Simulating Autonomous Pedestrians Navigation : A Generic Multi-Agent Model to Couple Individual and Collective Dynamics

Patrick Simo Kanmeugne
Université Pierre et Marie Curie
Laboratoire d'Informatique de Paris 6
patrick.simo-kanmeugne(at)lip6.fr

Aurélie Beynier
Université Pierre et Marie Curie
Laboratoire d'Informatique de Paris 6
aurelie.beynier(at)lip6.fr

ABSTRACT

In this paper, we focus on planning credible walking paths in real-time for a potentially highly congested crowd of autonomous pedestrians. For this purpose, we exploit the principle of least effort, applied to human navigation, which postulates that credible behaviours emerge as a function of the organism's propensity to minimize metabolic energy expenditure with respect to task, environment dynamics, and organism's constraints to action [17]. We therefore propose a consistent problem formulation for the navigation task where both individual and collective dynamics are taken into account. Each pedestrian is represented as a situated agent who tries to reach its destination by following energy efficient paths. Agents are autonomous, and at the same time, subject to the environment dynamics. They interact with each other through the environment in order to estimate their energy expenditure relatively to their tasks. Our formulation results in a generic and scalable multi-agent model, capable of simulating individual and collective behaviours regardless of the number of agents.

Keywords

pedestrian navigation, multi-agent simulation, interaction, coordination, traffic.

1. INTRODUCTION

Real-time pedestrian crowds simulation is a complex task for computer scientists. On the one hand, social studies on pedestrians' behaviours show that each pedestrian in a crowd behaves autonomously, conscientiously interacting with other pedestrians, while pursuing its own objectives [4]. On the other hand, empirical observations of pedestrians' flow in highly congested areas demonstrate some striking similarities between pedestrians' behaviours and particle flow dynamics [7].

Consequently to these apparently contradictory issues, designing philosophies diverge on whether to consider pedestrians' characteristics and local interactions, or to focus on pedestrians' flow regardless of individual characteristics, in order to formulate the underlying modelling principles. In the current literature, a naïve application of each of these philosophies is proved to lead to partially satisfying results. The first one could lead to intractable principles [9], resulting into models that struggle to reproduce collective behaviours like the edge effect [23] or the fingering effect [28]. The second philosophy could be inappropriate for low-density crowds, since it neglects pedestrian individualities, and might result into models that produce non-realistic individual behaviours [5].

In this paper, we explore the principle of least effort (PLE) [29] applied to human navigation, for a more generic approach. According to this principle, credible walking paths emerge as a function of the organism's propensity to minimize metabolic energy expenditure with respect to task, environment dynamics, and organism's constraints to action [17]. Several psychological studies on human movement showed that metabolic energy expenditure regulation is critical enough to explain both individual and collective behaviours among human beings [10, 29, 22, 17]. Following this idea, our contribution is:

1. a **consistent problem formulation** of the navigation task of autonomous pedestrians, where both individual and collective dynamics are taken into account. Pedestrians are situated agents who try to follow energy efficient paths towards their destinations. They use navigable resources, which recover the entire navigable space, to build their paths. Navigable resources mediates interaction between agents and provide dynamic measures that help the agents to estimate their energy expenditure relatively to their task.

2. a **generic multi-agent model**, in respect with our formulation, to perform real-time simulations of a potentially highly congested crowd. We will see that the *environment* concept from the multi-agent paradigm is particularly useful to tackle the complexity of the navigation task. The environment could be seen as an independent component that maintains dynamic measures used by agents to compute energy efficient paths. Moreover, since agents are situated in the environment and subjected to physical and dynamical constraints, an important part of the simulation dynamics could be delegated to the environment without compromising agents' autonomy.

Our work is close to IRM4S [15], continuum crowd [24] and PLEdestrian [5]. We use the same action theory as developed in the IRM4S model [15] and we adapt the agent model in order to fit the specificities of pedestrian navigation. Like Continuum crowd [24] and PLEdestrian [5], we use a least effort approach to model agents' behaviours and store dynamic information in the environment. However, the difference with our approach is that we specifically design the environment as a full component of the model, with a dedicated dynamics, different from that of agents.

We evaluate our work by submitting an online interview with videos of our model running on different low-density scenarios. We also run our model against some well known collective phenomenon – edge effect and fingering effect – with encouraging results in terms of credibility and scalability.

The rest of the document is organized as follows. In Section 2, we present related works on real-time pedestrians crowd simulation. In Section 3, we introduce our formulation of the navigation task for autonomous pedestrians. We also give an overview of the global architecture of our generic multi-agent model, and describe the role of each component. Sections 4 and 5 are respectively dedicated to the evaluation and the perspectives of our work.

2. RELATED WORK

Pedestrians crowd simulation is often tackled by using two types of approaches [21]: *microscopic* and *macroscopic* models.

Microscopic models are built upon pedestrians individual characteristics and local interactions, assuming that the combination of local interactions between agents – namely, collision avoidance mechanisms – and path following techniques, will result in the desired behaviour of the crowd. Helbing and Molnar [6] introduced the social force model (SFM) where each pedestrian is subjected to attractive or repulsive forces. For example, an attractive force could guide pedestrians toward their objectives, while a repulsive force keeps them away from obstacle or other pedestrians. The pedestrian dynamics is assumed to obey conservation laws, which leads to interesting collective behaviours. Reynolds [19] developed the concept of steering forces which are guiding forces that correspond to a pedestrian's preferences. For instance, a steering force could model the need to reach a predefined destination, to stay away from a given agent, or to stay close to a leading agent. Here, the agents dynamics do not obey any conservation laws, but the application of steering forces is ruled by a decisional architecture which is specific to each agent. The steering force paradigm is flexible and provides believable real-time animation [18]. Fiorini and Shiller [2] introduced the velocity obstacle paradigm which reduces the navigation problem of a mobile entity to the computation of an avoidance manoeuvre that ensures a collision-free navigation in a dynamic environment. Van den Berg et al. [26, 25] applied this paradigm and provided the RVO – Reciprocal Velocity Obstacle – model which is a robust adaptation for pedestrians real-time navigation.

One of the main challenge for microscopic model is the management of congestion [9]. Congestion management is more complex than simple collision avoidance since it involves both time and space considerations. It is also very critical because it influences the emergence of collective behaviours. To handle navigation in a congested area, microscopic models are often combined with global path planning techniques or mobile perception fields that helps the agent to perceive the dynamic features of the environment. Karamouzas et al. [13] used a dynamic uniform grid and couple a collision avoidance model with A^* path-planning techniques. The dynamic grid provides density occupation insights to the agents who can, therefore, plan to avoid occupied areas. Saboia et al. [20] modified the SFM model to introduce a mobile grid attached to each agent. The mobile grid allows the agent to change its desired velocity at reasonable time and to navigate through congested areas. Similar techniques could be found in [11].

Undoubtedly, using dynamic information on the environment density and fast global path-planning technique *speeds-up* the simulation – when an agent avoids occupied areas, this automatically reduces the calls to a collision avoidance algorithm, which is the most expensive operation in such simulations. Nevertheless, most microscopic models separate local collision avoidance from global path planning, and conflicts inevitably arise between these two competing goals. Those conflicts tend to be exacerbated in highly congested areas or highly dynamic environments [24].

Macroscopic models offer a more objective modelling framework, concerning these last issues, by representing the crowd as a whole. Hughes [9] investigated the analytic properties of human flow and propose the following hypothesis to define a continuous human flow model:

1. The walking speed of pedestrians is determined by the density of surrounding pedestrians, the behavioural characteristics of the pedestrians, and the ground on which they walk.

2. Pedestrians have a common sense (potential) of the task they face to reach their common destination, such that any two individuals at different locations having the same potential would see no advantage to exchange their locations.

3. Pedestrians seek to minimize their estimated travel time but temper this behaviour to avoid extreme densities.

Treuille et al. [24] managed the resulting equations for real time simulation and define a *dynamic potential function* to formalize the navigation as an optimization problem. The resulting potential function is exploited to generate a dynamic vector field that governs the overall crowd behaviour.

Obviously, the underlying principles of a macroscopic models leave little room for agents' autonomy. Myopic collision avoidance behaviours and difficulty to handle several agents with different destinations, are among the most relevant drawbacks of such approaches. Nonetheless, it is also obvious that those models produce much more believable collective behaviours for highly congested crowd. We argue that those good performances are due to a more coherent optimization framework. We believe that it is possible to reproduce a similar framework while preserving pedestrians autonomy. Thus, we propose a new framework that uses the multi-agent paradigm, and develop a consistent formulation of the navigation task for autonomous pedestrians.

3. COUPLING INDIVIDUAL AND COLLECTIVE DYNAMICS

In this section, we present the formulation of the navigation task for autonomous pedestrians and the full specification of our multi-agent model.

3.1 Formulation

Inspired by the work of Whittle [27], Guy et al. [5] explicitly formulated the metabolic energy spent by pedestrians when they walk:

$$E = mass \cdot \int (e_s + e_w \cdot |v|^2) \cdot dt \quad (1)$$

Where:

- v is the pedestrian's instantaneous velocity
- e_s and e_w are individual attributes, respectively equal to $2.23 \frac{J}{kg \cdot s}$ and $1.26 \frac{J \cdot s}{kg \cdot m^2}$ for an average human[1]
- $mass$ is the pedestrian's mass.

Kapadia et al. [12] extended this formula to include a specific *collision effort* which is the amount of energy that is expended through collisions:

$$E = mass \cdot \int (e_s + e_w \cdot |v|^2 + e_c \cdot c_p(t)) \cdot dt \quad (2)$$

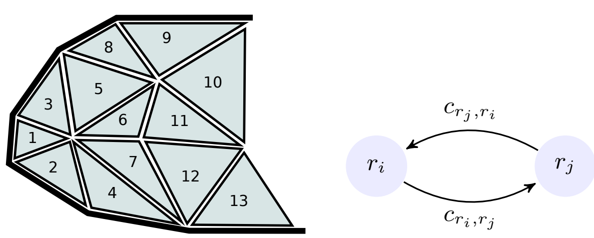
Where:

- $c_p(t)$ estimates the penetration depth of the collision if the agent is colliding with another agent at that point of time.
- $e_c = 10 \frac{J}{kg \cdot m \cdot s}$ is a penalty constant for collisions.

We formulate the navigation task of our agents in regards to this last equation: each agent will try to minimize it, individually and subjectively, by speculating on its surrounding's dynamics and adapting its walking behaviour accordingly.

3.1.1 Resources and Task

To support the navigation task, we assume a 2D continuous space which is discretized into contiguous triangular meshes of homogeneous size. Each triangular mesh is a *navigable resource* that will be used by agents to build their path.



(a) (b)

Figure 1: Structure of the continuous space. Each resource r_i is materialized by a triangular mesh. Each pair of resources (r_i, r_j) represents a discretized movement from r_i to r_j. The real-time cost of a discretized movement (r_i, r_j) is noted c_{r_i,r_j}.

Figure 1(a) gives an overview of the topological structure extracted from the continuous space. We choose triangular meshes because they allow us to recover the entire space with no discontinuities.

[1] J: Joules; kg: kilograms; m^2 : square meters

Our topological structure induces an oriented graph where each resource r_i represents a node, and each pair of contiguous resources (r_i, r_j) represents a *discretized movement*. We associate a real time cost c_{r_i,r_j} to each discretized movement (r_i, r_j), to be valued relatively to an agent: c_{r_i,r_j}, at a given time t, represents the average metabolic energy that the agent expects to spend if it travels from r_i to r_j at t (Figure 1(b)).

Consequently, a first formulation of the navigation task could be stated as: following the energy most efficient path available from a given position A towards a destination B, where the path is represented as a suite of contiguous resources $(r_i)_{1 \leq i \leq k}$, and the total energy of a path is estimated as the overall cost of the discretized movements that constitute it. This corresponds to the following decision problem:

$$\begin{cases} \text{find } (r_i)_{1 \leq i \leq k} \text{ such as} \\ A \in r_1 \\ B \in r_k \\ r_i \text{ and } r_{i-1} \text{ are contiguous } \forall i > 1 \\ \min \sum_{i=2}^{i=k} c_{r_{i-1},r_i} \end{cases} \quad (3)$$

With,

$$\begin{aligned} c_{r_{i-1},r_i} \quad = \quad & e_s \cdot D_{r_{i-1},r_i} + \\ & e_w \cdot S_{r_{i-1},r_i} \cdot |v_{r_i,r_{i-1}}|^2 + \\ & e_c \cdot D_{r_{i-1},r_i} \cdot (q_{r_i} + q_{r_j}) \end{aligned} \quad (4)$$

Where,

- D_{r_i,r_j} is a real time estimation of the mean total travel time from r_i to r_j including the potential delays due to congestion.
- S_{r_i,r_j} is a real time estimation of the mean travel time from r_i to r_j excluding the delays due to congestion.
- v_{r_i,r_j} is a real time estimation of the mean travel speed from r_i to r_j.
- q_{r_i} is a real time estimation of the mean number of agents in r_i.

Equation (4) corresponds to our estimation of the metabolic energy expenditure for a discretized movement, drawn from equation (2). As stated above, it represents the real time estimation of the amount of energy that the agent expects to spend if it travels from r_i to r_j. Here, we suggest that the number of expected collisions is proportional to the mean number of agents in both resources r_j and r_j. For simplicity, we have neglected the contribution of the mass and considered a constant penetration depth for collisions.

D_{r_i,r_j}, S_{r_i,r_j}, q_{r_i}, q_{r_j} and v_{r_i,r_j} are stochastic measures that are estimated relatively to an agent. Since they are closely related to the traffic, we also call them *dynamic information variables*. In the next section, we propose an explicit formulation of those variables. For that purpose, we introduce an independent traffic module which is in charge of converting the collective dynamics into individual utilities.

3.1.2 Converting Collective Dynamics into Individual Utilities

We assert that there is a straight analogy between the traffic within a navigable resource – namely, agents entrances and exits – and the queueing phenomenon [30]. Queueing theory is sometimes used in pedestrians flow simulation, especially in evacuation simulation [14]. This theory provides pragmatic mathematical tools to describe the quality of the traffic when many client users want to access a service provider with limited capacity. It is possible to estimate the quality of the traffic through stochastic measures like, *mean service times*, *mean delays*, *mean number of users*, etc., if the probabilities distribution of departure and arrival times of users are known.

Here, we assimilate a navigation resource to a *provider*, agents to *users*, and discretized movements to *services* provided by resources. If an observer watches the entrance and exit times of transiting agents within navigation resources during the simulation, we can derive the following measures relatively to the observer by exploiting the queueing theory (the exponent "o" means that the estimation is relative to the observer):

$$D^o_{r_i,r_j} = q^o_{r_i} \cdot \left(\lambda^o_{r_i,r_j}\right)^{-1} \quad (5)$$

$$S^o_{r_i,r_j} = \left(\mu^o_{r_i,r_j}\right)^{-1} \quad (6)$$

$$v^o_{r_i,r_j} = L_{r_i,r_j} \cdot \left(S^o_{r_i,r_j}\right)^{-1} \quad (7)$$

- $\lambda^o_{r_i,r_j}$ and $\mu^o_{r_i,r_j}$ represent respectively arrival and departure frequencies of users travelling from r_i to r_j
- $q^o_{r_i}$ is the mean number of users within r_i – equation (5) is derived from Little's formula [30, p. 85]
- L_{r_i,r_j} is the average length of (r_i, r_j)

An acceptable parallel would be therefore to associate an observer to each agent in order to derive the dynamic information variables relatively to agents. But for a real-time simulation perspective, this choice is risky in terms of memory use. This is why we introduce a single instance of a *traffic module*, that observes the arrival and departure of agents for each navigation resource, and compute dynamic information variables for them when requested. Agents interact with each others through the traffic module, by sending notifications when they enter or exit a navigation resource. Notifications are used by the traffic module to historize movements within each resource, and every agent can access dynamic information variables of resources that are within its *sensor range*. Note that it is possible to distribute several modules over the navigable space in order to process notifications efficiently.

Finally, we use (8) and (9) to consider agents' individual parameters in the explicit formulation of our dynamic information variables.

$$q_r = q^o_r \quad (8)$$

For any dynamic variable M_{r_i,r_j}:

$$M_{r_i,r_j} = M^{\perp}_{r_i,r_j} + \frac{q_{r_i} + q_{r_j}}{2 \cdot q_{max}} \cdot \left(M^o_{r_i,r_j} - M^{\perp}_{r_i,r_j}\right) \quad (9)$$

- $M^o_{r_i,r_j}$ is the value of the variable as computed by the traffic module
- $M^{\perp}_{r_i,r_j}$ is the value of the variable computed by the agent as if there was no traffic within r_i and r_j – i.e. by considering only its individual parameters and topological data. Note that if we assume V_{pref} as the preferred velocity of an agent from r_i to r_j, we can derive:

$$D^{\perp}_{r_i,r_j} = \frac{L_{r_i,r_j}}{V_{pref}} \quad (10)$$

$$S^{\perp}_{r_i,r_j} = D^{\perp}_{r_i,r_j} \quad (11)$$

$$v^{\perp}_{r_i,r_j} = V_{pref} \quad (12)$$

- q_{max} is the maximum possible size of the resource (number of users)

Note that equation (9) formalizes two intuitive facts:

1. The more relevant the traffic, the more macroscopic is the measure of the variable
2. The less relevant the traffic the more individual is the measure.

In the next section, we present the specification of a generic multi-agent model that performs real-time simulations according to our formulation.

3.2 A Generic Multi-Agent Model

A key point for the specification of our model is the action theory to be used to implement the situated agents' behaviours. Our approach relies on the *influence reaction principle* proposed in [1], where there is a clear distinction between influences, which are produced by agents' behaviours, and the reaction of the environment. Precisely, our model specification is inspired from the IRM4S – Influence Reaction Model for Simulation [15] – which is a concretization of [1]'s theory for real-time simulation. In IRM4S, two distinct dynamics are coupled: *agents* generate influences to modify their representation in the environment, and *environment* reacts to all influences according to *natural laws*, and updates all the agents' representations. Here, we adapt the environment architecture to include a physics engine that updates agents' representations and a traffic module that mediate interaction between agents.

Figure 2 represents the global architecture of our framework.

The **physics engine** is responsible for the dynamics of agents' bodies. It updates bodies' positions and instantaneous speeds with respect to influences provided by agents, and accounts for shocks and collisions.

The **traffic module** is responsible for the dynamic information variables maintenance. It defines the topological structure that represents the continuous space, and mediate interactions between agents while they navigate.

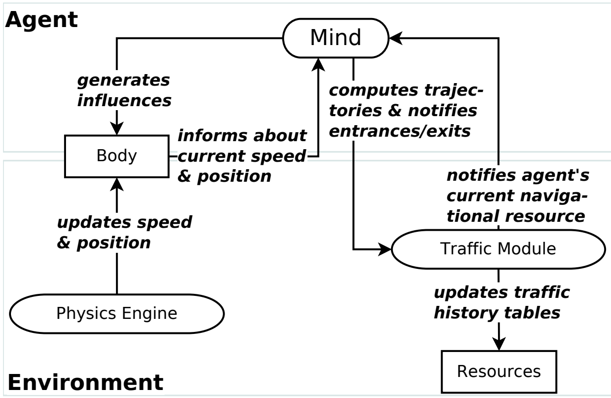
An **agent** is a relationship between a **mind** and a **body**. The mind dynamically maintains the energy most efficient path, relatively to the agent, and influences the body to follow the path until it reaches the destination.

We now detail the most important features of the model.

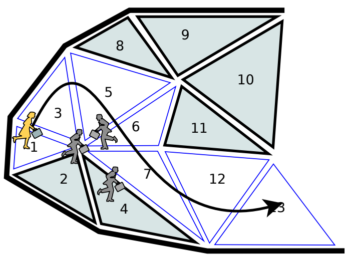
3.2.1 Agent

Our agent's model defines a *dynamic search algorithm* and an *influences set generation process* that guide the body towards the agent's destination.

The dynamic search algorithm starts from a current path and iteratively applies elementary moves, that consists in



(a) Architecture of our generic multi-agent model



(b) Presentation of the descriptive elements of an agent behaviour : the connected clear meshes represent the path of the agent. The bold curved arrow is the set of influences to be applied.

Figure 2: Overview of our generic multi-agent model

replacing links (discretized movements) in the current path, with alternative links in order to generate a more efficient path. Links replacement concerns only the resources that are sensed by the agent at the beginning of the search process. We experienced that such a dynamic search could be implemented efficiently by using an evolutionary search heuristic with a limited number of iterations [3]. Due to the lack of space, we do not detail the specification of this algorithm in this paper. We mostly focus on the architecture of the model.

An influences set could be visualized as a curved line that links the current agent's position with the farthest sensed resource on the path – see Figure 2(b). It formally represents the preferred velocities that the agent would take to reach its destination. The influences set computation could be handled by any linear interpolation algorithm.

To apply an influence to the body, the mind iteratively executes the algorithm 1. It selects the first influence from the current influences set and apply it to the body as the preferred velocity. When the body's position is updated by the physics engine, the mind notifies its movement to the traffic module which notifies back the travelled resources in order for the mind to update its path and, therefore, the current influences set.

3.2.2 Physics Engine

The physics engine updates bodies' positions and instantaneous speeds according to the velocity obstacle paradigm.

Algorithm 1: Application of influences

Data:
pos: mind's current assumed position ;
I: ordered set of influences ;
path: current path ;

Select the first influence from I, V_{pref} ;
Set V_{pref} to the body as the preferred velocity ;
Get the new position pos^{new} computed by the physics engine ;
Notify the traffic module with (pos, pos^{new}) to get the travelled resources ;
Update *path* according to the travelled resources ;
Update I ;
Set pos^{new} as the mind's assumed position ;

Given a preferred speed it computes the closest instantaneous velocity that allows a collision-free navigation in regards to all the dynamic obstacles.

3.2.3 Traffic Module

The traffic module updates *traffic history tables* of the resources according to a *history time step*. A *traffic history table* is a sliding window of predefined length that historizes agents' notifications. Two types of traffic history tables are associated to resources : *size* history table, to be used to estimate the mean number of users within the resource, and *transition* history tables, to be used to evaluate arrival or departure frequencies – a transition history table is associated to each discretized movement. When the traffic module is notified by an agent – with the mind's assumed position and the body's new position – it builds back the travelled resources chain to the agent, and stores them in a notification list. The notifications list is then processed at each history time step to maintain the traffic history tables of the travelled resources. We use a temporary classification for travelled resourced, labelled "*Active*", to process notifications efficiently. *Active* resources are resources that contains non zero values in their respective traffic history tables. At each history time step, only *Active* resources are maintained according to the algorithm 2.

4. EVALUATION

We have implemented our model in C++ on a standard MS machine – Intel E6550 dual core with a 2.33GHz processor and 2GB of memory – and carried out some experiments that highlight the most interesting features of our work, comparing to classical microscopic models. We have chosen the latest version of the RVO model, optimized for collision avoidance and CPU performances [25], to run series of comparative evaluations on selected benchmarks. The RVO model exploits the velocity obstacle paradigm as the underlying navigation principle, and performs within a multi-agent framework. We used the same type of collision avoidance algorithms to design a physics engine that matches our specification. The discretization of the space into triangle meshes has been realized with the freefem++ software [2]. Here, agents are physically represented as 2d disks of predefined radius and each resource cannot contain more than four agents.

[2]www.freefemplusplus.org

Algorithm 2: Traffic history table maintenance

```
Data:
Actives: "Active" resources list ;
Notifications : list of the travelled resources ;
foreach r ∈ Actives do
    Set the current history index value to 0 for every
    traffic history table of r ;
end
foreach c ∈ Notifications do
    Update Actives with the new travelled resources ;
    if |c| == 1 then  /* c has only one resource r_c */
        Q(r_c) ← size history table of r_c;
        increment the current history index value of
        Q(r_c) ;
    else  /* c has discretized movements (r_i, r_j) */
        foreach (r_i, r_j) ∈ c do
            T^{r_j}(r_i) ← transition history table of (r_i, r_j);
            Q(r_j) ← size history table of r_j;
            Q(r_i) ← size history table of r_i;
            decrement the current history index value of
            Q(r_i) ;
            increment the current history index value of
            T^{r_j}(r_i) ;
            increment the current history index value of
            Q(r_j) ;
        end
    end
end
Ignore non "Active" resources for the next step ;
```

We conducted two types of evaluations:

1. an online interview: we have invited volunteers to compare the performances of both model on low-density scenarios.
2. a validation of two well-known collective behaviours witnessed in highly congested crowds: the edge [23] and the fingering effects [28]

4.1 Online Interview

We have uploaded an online interview [3] to compare both models on several scenarios among the most frequently mentioned – see [12]. For each scenario, a pair of videos showing the performances of our model (labelled "GMAM") and RVO has been uploaded, and participants were invited to assign a comparative note among the following:

1. "none": **none** of the video is credible.
2. "++ credible": the left/right side video is **much more** credible
3. "+ credible": the left/right side video is **more** credible
4. "equally credible": both videos are **equally** credible

To ensure an objective comparison, the underlying model for each video has been hidden to participants, and videos were presented in a random order from one scenario to another. Figure 3 presents the results of the interview for the following benchmarks :

1. *"Same Direction"*: a group of pedestrians walking in the same direction
2. *"Crossing"*: a crossing between two groups of pedestrians walking in opposite directions
3. *"Fast and Slow"*: a fast pedestrian walking behind a group of slow pedestrians
4. *"Narrow Passage"*: a group of pedestrians taking a narrow passage

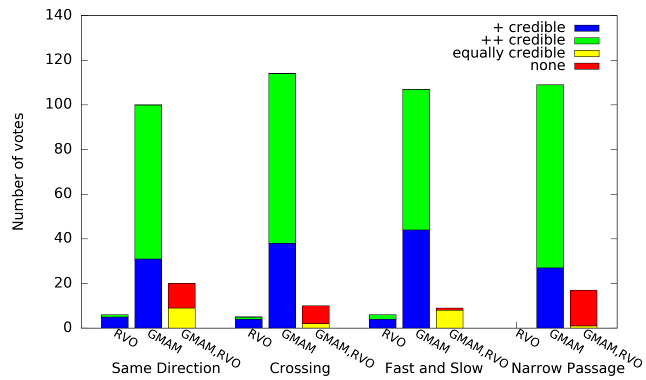


Figure 3: Results of the online interview. Our model is labelled as "GMAM"

A total of 140 participants completed the interview. Most of them (73%) were students or academics from our university. Results of the interview show that participants massively classified our model as the most credible for the given benchmarks. Hereinbelow, we justify the most relevant features of our model comparing to RVO.

1. *"Same Direction"*: our agents plan away from lateral and front resources for more efficiency. This results into emergent *V-like patterns* that we can witness in real life [16].
2. *"Crossing"*: less occupied and more fluid resources offer a better individual utility according to our formulation of the navigation task. As result, our agents prefer such resources in this benchmark and self-organize into *unidirectional lanes*.
3. *"Fast and Slow"*: the fastest agent, in our model, *overtakes* as soon as it gets close to the slow pedestrians group while the RVO agent passes in the middle of the group. Our agent plans for the surrounding resources, since they have better utility values relatively to its preferred speed.
4. *"Narrow Passage"*: The more agents arrive at the entrance of the passage, the more the entrance's surrounding resources become congested. As result, our agents steer back to avoid congested areas at the entrance of the passage, while RVO agents spread laterally on the borders.

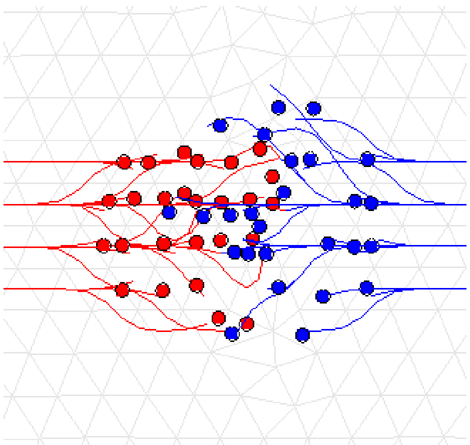
Next, we evaluated the performances of both models against two well-studied collective behaviours:

[3] www-desir.lip6.fr/~simokanmeugne/evaluation0.html

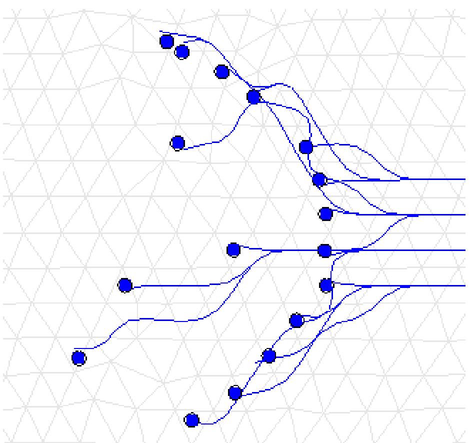
1. Edge effect: for unidirectional flows of pedestrians, *sides move faster than the center of the crowd* [23, 5, 20].
2. Fingering effect: for bidirectional flows, *pedestrians self-organize into unidirectional lanes to limit conflicts with the oncoming flow* [23, 28].

4.2 Collective phenomenon

Figures 4(a) and 4(b) illustrate how our model renders the fingering effect and the edge effect for low-density scenarios. The goal of this second evaluation is to generalizes the results for highly congested crowds.



(a) Fingering effect



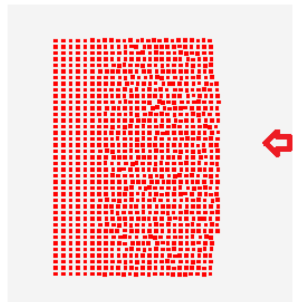
(b) Edge effect

Figure 4: Illustration of our model performances against the edge effect (b) and the fingering effect (a) for low-density scenarios. Agents and their influences sets are coloured according to the direction of the movement. Here, the blue colour is for agents moving from the left to the right and the red colour, for agents moving from the right to the left.

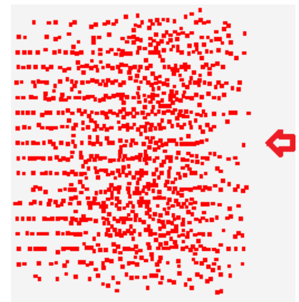
To reproduce highly congested crowds for this second evaluation, we realized four simulations of one thousand agents in restricted areas : for the edge effect, one thousand agents moving in the same direction, and for the fingering effect, a crossing between two groups of five hundred agents moving in two opposite directions. Figure 5 gives an overview of the differences between the performances of both models.

We can see that our model (Figures 5(b) and 5(d)) matches the descriptions of the collective behaviours better than RVO (Figures 5(a) and 5(c)).

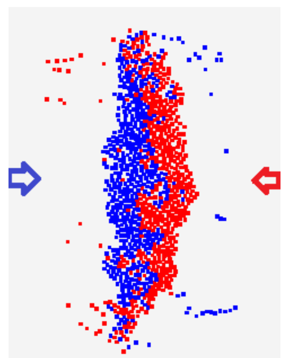
Figure 5(d) illustrates self-organization into unidirectional lanes. Figure 5(b) shows side agents deviating from the center of the crowd and a more important concentration of agents in the middle of the crowd. These are encouraging results which prove that our model can produce credible results even for highly congested crowds.



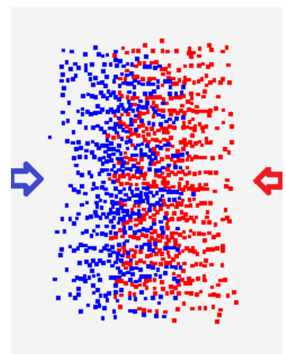
(a) Edge Effect: RVO



(b) Edge Effect: GMAM



(c) Fingering Effect: RVO



(d) Fingering Effect: GMAM

Figure 5: Validating the fingering effect and the edge effect

5. CONCLUSION AND PERSPECTIVES

We proposed a generic multi-agent model for real-time simulation of a potentially highly congested crowd of autonomous pedestrians. We are interested in reproducing credible walking paths in real-time regardless of the number of agents. Our model originates from the principle of least effort applied to human walking behaviours and uses the influence and reaction principle to implement agents' behaviours. Agents communicate through a traffic module to dynamically maintains energy efficient paths, while being subject to a physics engine which updates their positions and instantaneous speeds.

The different experiments that we have made show encouraging results in terms of credibility. The dynamic planning algorithm that we used in combination with a traffic module give more insight to the agents and favours the emergence of complex individual and group behaviours like overtaking and V-like formations. Moreover, our model performs better than a classic microscopic model (RVO) when the number of agents increases, and reproduces some well-known collective behaviours like the fingering and the edge effect.

As short-term perspectives, we intend to work on the dynamics search calibrations in order to evaluate our work in terms of CPU performances. As mean-term perspectives, it could be interesting to study resource aggregation techniques to allow hierarchical planning. Deducing dynamic information for aggregated resources could be done the same way as for elementary resources, i.e. computed from agents' notifications. Also, we want to extend our formulation in order to account for time constraints and emergency situations. The concept of generalized cost developed in [8] provides interesting insights for that purpose. A long-term perspective is to work on the concept of *resource policy* to describe complex resource in terms of service quality. A resource policy could describe how a resource should be used. This could be helpful to elaborate richer urban simulations and integrate complex transports facilities like escalators, elevators, etc.

6. REFERENCES

[1] J. Ferber and J.-P. Müller. Influences and reaction: a model of situated multiagent systems. In *Proceedings of Second International Conference on Multi-Agent Systems (ICMAS-96)*, pages 72–79, 1996.

[2] P. Fiorini and Z. Shiller. Motion planning in dynamic environments using the relative velocity paradigm. *[1993] Proceedings IEEE International Conference on Robotics and Automation*, 1993.

[3] F. Glover and M. Laguna. Tabu Search. *Journal of computational biology a journal of computational molecular cell biology*, 16(12):1689–703, 1997.

[4] E. Goffman. The Individual As A Unit. Relation in Public: Microstudies of the Public Order. *Allen Lane The Penguin Press*, 1972.

[5] S. J. Guy, J. Chhugani, S. Curtis, P. Dubey, M. Lin, and D. Manocha. PLEdestrians : A Least-Effort Approach to Crowd Simulation. *Computing*, pages 119–128, 2010.

[6] D. Helbing and P. Molnar. Social Force Model for Pedestrian Dynamics. *Physical Review E*, 51(5):4282–4286, 1998.

[7] D. Helbing, P. Molnár, I. J. Farkas, and K. Bolay. Self-organizing pedestrian movement. *Environment and Planning B Planning and Design*, 28(3):361–383, 2001.

[8] S. P. Hoogendoorn and P. H. L. Bovy. Pedestrian route-choice and activity scheduling theory and models. *Transportation Research Part B: Methodological*, 38(2):169–190, 2004.

[9] R. L. Hughes. A continuum theory for the flow of pedestrians, 2002.

[10] C. L. Hull. Principles of behavior: An introduction to behavior theory. 1943.

[11] M. Kapadia, S. Singh, W. Hewlett, and P. Faloutsos. Egocentric affordance fields in pedestrian steering. *Proceedings of the 2009 symposium on Interactive 3D graphics and games I3D 09*, 1(212):215, 2009.

[12] M. Kapadia, M. Wang, G. Reinman, and P. Faloutsos. Improved benchmarking for steering algorithms. In *Motion in Games*, pages 266–277. Springer, 2011.

[13] I. Karamouzas, R. Geraerts, and M. Overmars. Indicative routes for path planning and crowd simulation. *Proceedings of the 4th International Conference on Foundations of Digital Games FDG 09*, 45:113, 2009.

[14] G. G. Lovas. Modeling and simulation of pedestrian traffic flow. *Transportation Research Part B: Methodological*, 28(6):429–443, 1994.

[15] F. Michel. The IRM4S model: the influence/reaction principle for multiagent based simulation. In IFAAMAS, editor, *6th international joint conference on Autonomous agents and multiagent systems*, pages 903–905, Honolulu, Hawai'i, USA, 2007. ACM.

[16] M. Moussaïd, N. Perozo, S. Garnier, D. Helbing, and G. Theraulaz. The walking behaviour of pedestrian social groups and its impact on crowd dynamics. *PloS one*, 5(4), 2010.

[17] K. M. Newell and W. A. Sparrow. Metabolic energy expenditure and the regulation of movement economy, 1998.

[18] J. Ondrej, J. Pettré, A.-H. Olivier, and S. Donikian. A synthetic-vision based steering approach for crowd simulation. *ACM Transactions on Graphics*, 29(4):1, 2010.

[19] C. Reynolds. Interaction with Groups of Autonomous Characters. *Group*, 21(4):449–460, 2000.

[20] P. Saboia and S. Goldenstein. Crowd simulation: applying mobile grids to the social force model. *The Visual Computer*, 28(10):1039–1048, 2012.

[21] A. Schadschneider, W. Klingsch, H. Kluepfel, T. Kretz, C. Rogsch, and A. Seyfried. Evacuation Dynamics: Empirical Results, Modeling and Applications. 2008.

[22] W. A. Sparrow. The efficiency of skilled performance. *Journal of motor behavior*, 15(3):237–261, 1983.

[23] G. K. Still. *Crowd dynamics*. PhD thesis, University of Warwick, 2000.

[24] A. Treuille, S. Cooper, and Z. Popović. Continuum crowds. *ACM Transactions on Graphics*, 25(3):1160, 2006.

[25] J. Van Den Berg, S. Guy, M. Lin, and D. Manocha. Reciprocal n-body collision avoidance. *Robotics Research*, pages 1–16, 2010.

[26] J. Van Den Berg and D. Manocha. Reciprocal Velocity Obstacles for real-time multi-agent navigation. *2008 IEEE International Conference on Robotics and Automation*, pages 1928–1935, 2008.

[27] M. W. Whittle. *An Introduction to Gait Analysis*. Butterworth-Heinemann, 2007.

[28] J. Zhang, W. Klingsch, A. Schadschneider, and A. Seyfried. Ordering in bidirectional pedestrian flows and its influence on the fundamental diagram. *Journal of Statistical Mechanics: Theory and Experiment*, 2012(02):P02002, 2012.

[29] G. K. Zipf. *Human behavior and the principle of least effort: An introduction to human ecology*, volume 47. Addison-Wesley Press, 1949.

[30] M. Zukerman. Introduction to Queueing Theory and Stochastic Teletraffic Models. *Networks*, 2008:1–218, 2008.