Activation of the Following Mode to Simulate Heterogeneous Pedestrian Behavior in Crowded Environment

Laure Bourgois[1], Thomas Heckmann[1], Emmanuelle Grislin-Le Strugeon[2] and Jean-Michel Auberlet[1]

[1] *Université Paris Est, IFSTTAR-IM-LEPSIS, 53 Bd Lefebvre, 75732 Paris, Cedex 15, France*

[2] *Université Lille-Nord de France et LAMIH-UMR 8201, Université de Valenciennes, Le Mont Houy, 59313 Valenciennes Cedex, France*

Keywords: Agent, Simulation, Pedestrian Model, Navigation, Following Mode.

Abstract: To simulate pedestrian crowds, most of the current studies use the microscopic approach, in which the pedestrian is modeled as an individual entity. With the microscopic approach, the heterogeneity in the pedestrian population is mostly based on inter-individual difference in the agent model parameters, like speed, destination, etc. In fact, what can be seen in congested real situations, is some pedestrians choosing to temporarily follow other ones in order to facilitate the flow while going on avoiding collisions. Each pedestrian can choose to adopt and leave such a behavior according to his/her individual and local situation. In order to model and simulate this behavior, we propose to include in the pedestrian agent navigational model a decision process that allows to activate the following task in addition to the collision avoidance task. The decision depends on the agent's internal state and on what it perceives in its environment. Our proposition is an attempt to define the conditions that must trigger the switching to another navigation mode, and the selection of the other agent to be followed, i.e. the "leader".

1 INTRODUCTION

The microscopic approach is widely used for modeling pedestrian crowds; each pedestrian is seen as an individual and independent entity. The agent's navigation behavior, independently from the continuous or discrete environment representation, results then from a sum of forces (Helbing and Molnar, 1995) or from a set of rules (Reynolds, 1987). In comparison to the macroscopic approach based on flow models and used to assess pedestrian quantities, the microscopic approach is appropriate to predict interactions and behavioral adaptation in a group.

One drawback of the actual microscopic approach is its relative poorness for modeling heterogeneity in the pedestrian population. Indeed the inter-individual difference between pedestrians lie in the agent model parameters, like shoulders size, speed, destination, etc. In real life, it is usual to observe in congested situations that some pedestrians choose to temporarily follow other ones in order to facilitate the flow while going on avoiding collisions. Thus, each pedestrian can choose to adopt and leave such a behavior according to his/her individual and local situation. This is the phenomenon we want to model and simulate.

Our aim is thus to include in the pedestrian agent navigational model a decision process that allows to switch between the collision avoiding behavior and a behavior that combines two moving modes, i.e. the collision avoiding and the following modes. The decision depends on the agent's internal state and on what it perceives in its environment. The difficulty is to define the conditions that must trigger the switching to another navigation mode, and then to define the other agent to be followed, i.e. the "leader".

The rest of the article is organized as follows. Section 2 presents related works based on the microscopic approach in the pedestrian modeling and simulation field. Section 3 explains the global model that makes the context of our works, then details the part of the model proposed here and dedicated to the following task. The proposition has been implemented and has been the subject of first evaluations reported in section 4, before conclusion.

2 RELATED WORKS

In the microscopic approach, two main categories of models can be used to simulate pedestrian move-

Bourgois L., Heckmann T., Grislin-Le Strugeon E. and Auberlet J..
Activation of the Following Mode to Simulate Heterogeneous Pedestrian Behavior in Crowded Environment.
DOI: 10.5220/0004195101780183
In *Proceedings of the 5th International Conference on Agents and Artificial Intelligence* (ICAART-2013), pages 178-183
ISBN: 978-989-8565-38-9

ments: the models based on behavioral rules and the models based on physical rules.

In the first category, the most known is the Boids model, introduced in (Reynolds, 1987), used first to simulate coordinated animal motion such as bird flocks and fish schools, and then crowd path following behaviors. Such models are based on the combination of multiple behaviors (e.g., obstacle avoidance, path following and entity separation), either by switching between them (an action selection problem) or by blending when they are compatible (e.g., see (Hanon et al., 2003)). The global model of the autonomous character is composed as a hierarchy of three layers: action selection (strategy), steering (path determination), and locomotion (animation). This produces group behaviors with homogeneous behavior inside the group. In comparison, we try to develop the possibility to get more differentiated behaviors.

Another model based on a set of behaviors is presented in the CROWD-MAGS project (Moulin and Larochelle, 2010), with a tool to model and simulate crowds. The behaviors are complex and represented by hierarchical rules. The objective is to extend existing models with the help of the explicit notion of social cohesiveness: any agent knows it belongs to a group and its decisions depend on this knowledge. Group membership is determined by a cognitive process (e.g., based on the aggressiveness feeling). In comparison, our aim is to model crowd made of anonymous persons, with low level interactions.

In the second category of models, a well-known model is the Social Force Model (SFM) by Helbing and Molnar (Helbing and Molnar, 1995). This model describes a pedestrian in a crowd as an entity subject to attractive forces (e.g., its destination, the other entities in the same group) and repulsive forces (e.g., walls, other external entities). The model is widely used for reasons of simplicity and extensibility, each author providing specific parameters depending on the situations to be simulated. Social forces are for example used to simulate pedestrian dynamics in the Floor Field models (Schadschneider et al., 2002) in the context of discretized environments (cellular automata). However, SFM involves limitations, because it is essentially a reactive model, with passive perception and homogeneous pedestrian interactions.

Teknomo adds a second order term to manage collisions in a similar model, based on the social force notion (Teknomo, 2009), but with the same limitations. Recent works (Moussaid et al., 2010), derived from the Helbing's model, present common characteristics with the CROWD-MAGS project cited above, because they include similar knowledge, or awareness, of group membership. The aim is to simulate, by the use of attractive forces, some recurrent patterns observed while groups are formed and their influence on the crowd flow. For the same reason as for the CROWD-MAGS, this does not match our aim. Qiu's work (Qiu and Hu, 2010) simulates crowd behaviors either. Inside a group, the influence of the group members is used to define the individual position and moving direction. The model provided by Hoogendoorn (Hoogendoorn and Bovy, 2000)(Hoogendoorn and Daamen, 2005) used concepts from the control theory. In this model, the pedestrian optimizes a utility function computed from costs associated to acceleration, spatial proximity and path diversion. The pedestrian architecture includes three levels:

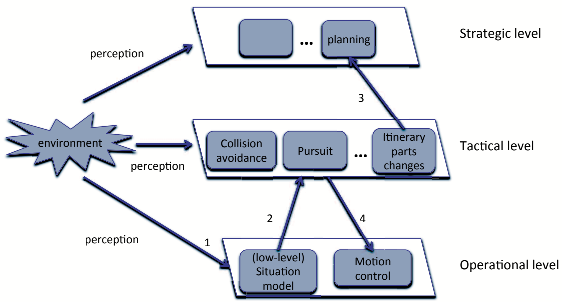

Figure 1: General model of the pedestrian agent.

- the strategic level, for long-term decision, like itinerary planning;
- the tactical level, for middle-term decision, like path or interaction type selection;
- the operational level, for short-term action, like instantaneous physical motion.

Hoogendoorn suggests to make the levels collaborate, but without any formalization, nor precise description. However, this architecture provides a structure that offers common points with the human behavior modeling, as Allen's driving task model (Allen et al., 1971), and thus can facilitate the integration of results from this domain.

3 THE PEDESTRIAN MODEL

Our model of the pedestrian agent includes three levels — the strategic, tactic and operational levels — described in Fig. 1, adapted from the hierarchical architecture proposed by Hoogendoorn (Hoogendoorn and Bovy, 2000). Our purpose concerns more precisely the tactical and operational levels.

We propose a model in which the agent's behavior results from inter-levels and intra-level interactions. At the operational level and with the perceived data (1 in Fig. 1), the agent updates its representation of the current situation, including its own state. The identified situation (2 in Fig. 1) is used at the tactical level to select one of the navigation tasks and can be used to move up to the strategic level if itinerary modification is needed (3 in Fig. 1). Once a navigational task is selected, the control returns to the lowest level for the agent's motion (4 in Fig. 1). The perception process of our model has been detailed in previous works (Bourgois et al., 2012). In this paper, we detail the selection of the navigation task, and more specifically the conditions to activate the following task in a crowded environment.

3.1 Navigation Tasks

In our model, the physical and internal states of the pedestrian agent p are based on the Social Force Model from Helbing (Helbing and Molnar, 1995) and on the notation by Hoogendoorn (Hoogendoorn and Daamen, 2005). We define the behavior $b_p(t)$ of the pedestrian agent p at time t by three components, which are the agent's physical state $S_p(t)$, goal G_p and behavioral thresholds T_p:

$$b_p(t) = (S_p(t), G_p, T_p)$$

The agent's physical state is defined at time t by its location $r_p(t)$, velocity $v_p(t)$ and direction vector $\vec{d}_p(t)$:

$$S_p(t) = (r_p(t), v_p(t), \vec{d}_p(t))$$

The agent's internal state is only detailed concerning the agent's goal, which is assumed to be invariant during the simulation and defined by a final location d_p and a desired velocity (free speed) v_p^*:

$$G_p = (d_p, v_p^*)$$

The behavior of the agent p is parameterized according to a set of thresholds T_p that determine its reaction to the current situation. In previous works (Bourgois et al., 2012), we have defined the intensity and the sensibility thresholds that are used to quantify the force exerted by an agent on another. Our aim is here to study a sub-set of T_p dedicated to the following task.

3.2 Activation of the Following Task

At the tactical level, we focus on two tasks included in the navigation activity and that can be antagonist: the collision avoidance task and the following task. The agent activates these tasks according to its internal state and the surrounding situation. Particularly, the following task is triggered by the decision process on the base of the population density in the agent's neighborhood, and the agent's velocity and direction.

At time t, three factors are combined to change the internal state, and lead to make the decision: one situational factor, which is the agent p's neighborhood density $N_p(t)$; two self-awareness factors, which are the difference from the agent's direction $\vec{d}_p(t)$ to its ideal direction $\vec{d}_p^*(t)$ (calculated on the base of its final location goal d_p) and the difference from the agent's velocity $v_p(t)$ to its ideal velocity v_p^*. The values of these factors are compared to three associated thresholds to decide on the following task activation:

- s_p^N is the neighborhood density threshold,
- s_p^d is the direction threshold, and
- s_p^v is the velocity threshold.

The activation of the following task depends on three conditions relatively to these thresholds:

`if` $(N_p(t) > s_p^N)$
`and` $(|\vec{d}_p(t) - \vec{d}_p^*(t)| < s_p^d)$
`and` $(|v_p(t) - \frac{\sum_i^{N_p(t)} v_i(t)}{N_p(t)}| < s_p^v)$ `then`
  `leader` $\leftarrow$ *`selectLeader();`*
  `if (leader exists) then`
    `activateFollowingTask();`

We point out that the agent can decide to activate the following mode, but in some case, it can not find a leader. Indeed, the following task is composed of two process, one to recognize the situation and one to choose the most relevant one to follow. The first condition to trigger the following mode is to exceed a defined amount of neighbors. The pedestrian density $N_p(t)$ that is taken into account at time t by the agent p in its neighborhood is computed on the base of a relevance distance. We have evaluated this relevance distance in previous works (Bourgois et al., 2012), in which we have shown that the set of neighbors really taken into account varies according to the raw number of neighbors perceived by the agent in its field of vision: higher is the raw number of neighbors perceived, smaller is the radius at which the neighbors are taken into account. The relevance distance has been empirically determined according to the raw number of neighbors perceived by the agent in a 9m-deep field of vision. The second condition to trigger the following mode is to go close enough to the ideal direction. This condition defines the maximal difference between the current direction and the ideal direction. When the condition is not validated, the agent is currently steering towards a point that is too far from the ideal to benefit from the following mode.

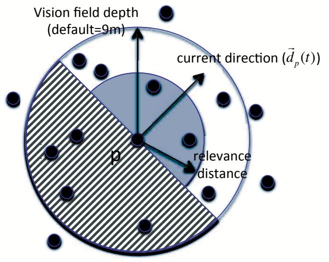

Figure 2: Vision and relevance fields from pedestrian p viewpoint. Pedestrians are represented by the (small) circles.

The third condition to trigger the following mode is to have a velocity that is close enough to the average velocity in the neighborhood. This condition defines the maximal difference between the agent's current velocity and the average velocity of its neighbors. When the condition is not validated, the agent is supposed to be either too slow or too fast to be able to follow its neighbors. However, the condition can make the agent lose the opportunity to follow one member in the group that would be faster than the others.

The potential leaders are then the other agents that are located in the half-circle whose radius is the relevance distance (Cf. Fig. 2). To start the following activity, one of these agents must be selected as the leader. We have studied three criteria that can be relevant to make the selection:

1. the distance: the leader is the one that minimizes the difference between its location and the agent's current location (i.e., $r_p(t)$);
2. the direction: the leader is the one that minimizes the difference between its direction and the agent's ideal direction (i.e., $\vec{d}_p^*(t)$);
3. the velocity: the leader is the one that minimizes the difference between its velocity and the agent's current velocity (i.e., $v_p(t)$).

For example, in Fig. 3, with two potential leaders at a relevant distance from the agent p, the agent a would be chosen to be the leader if the direction is used as the unique selection criterion; it would be the agent b if the distance is used as the criterion. Another possibility would be to combine these criteria. If two leaders can be chosen, then the first in the list is selected.

Finally, we remind that this activation process is made at each step of the simulation. Thus to deactivate the following task is equivalent to not activate the task.

3.3 The Following Task

When the following task is activated, our model calculates a sum of forces: the repulsive one are computed according to the standard SFM but the attractive one is now determined by the leader. Obviously, the chosen leader is not taken into account in the calculus of the repulsive forces. Therefore, in the following task, the final destination is momentarily replaced by the follow-up of the leader. In such a way, one pedestrian agent may have at its disposal a new temporary destination at every time step. We point out that this solution is a preliminary one; in this paper we focus on the conditions of the activation of the following mode. Moreover, this solution handles the following case: if an obstacle suddenly interferes in the trajectory of one agent then a repulsive force is applied on the agent by this obstacle as in the standard model. The following section details our first results.

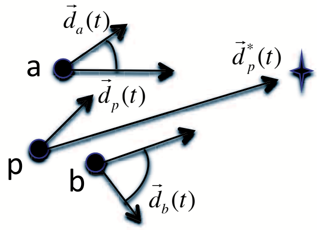

Figure 3: Selection of the leader to be followed by pedestrian p.

4 SIMULATION AND FIRST EVALUATIONS

In these experiments and as a first attempt, we have evaluated the relevance of each leader selection criterion (i.e., distance, direction and velocity) separately.

To create easily a sufficient density value, the environment constrains the agents to move in a 10m width by 60m length corridor. The input generates 6000 pedestrians per 30 simulated mn on the base of a Poisson law. This rate is considered to be realistic because it is consistent with the study in (Huat et al., 2005) that refers to Fruin's book (Fruin, 1971).

4.1 Model Variants Evaluation

At first, the thresholds related to the following mode are parameterized with the values: $s_p^N = 2$ pedestrians, $s_p^d = 15°$, and $s_p^v = 0.6\ m.s^{-1}$. We have collected the simulation data in a 30m width window in the middle of the corridor to have a stable situation, without noise due to pedestrian generation or to destination reaching.

Then three variants of the model based on three different *selectLeader* functions have been evaluated,

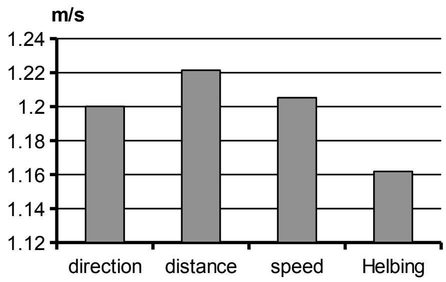

Figure 4: Pedestrians' average velocity in the three variants of our model and in the Social Force Model.

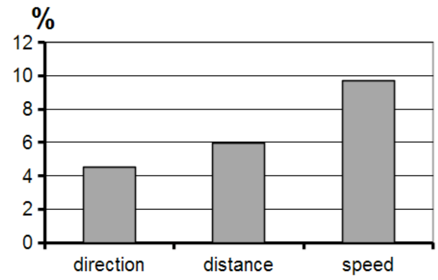

Figure 5: Gain in the pedestrians' average number of collisions (in %) in the three variants of our model compared to the Social Force Model taken as reference.

according to the three possible criteria for the selection. The following measures are used for the evaluation:

- average velocity,
- average itinerary length,
- average collision number.

The two first measures are frequently used as performance indicators to evaluate or validate traffic models. We see the last one as a quality (or resp. error) indicator. Indeed, it has been demonstrated that the Helbing's model allows the pedestrians to choose positions that are sufficiently close to create collisions (i.e., having a non empty intersection of their occupying ground surface). We calculate then the number of collisions with the intent to consider the smaller number the best.

The results of these experiments are the following.

- In the evaluated situation, which is congested, our model enables to improve the pedestrians' velocity, whatever the variant is used, compared to the Helbing's model alone (see Fig. 4). The distance variant gives the best results among the three variants when evaluated by the velocity criterion.
- Using the average collision number criterion, our model provides significative improvements compared to the Helbing's model alone (see Fig. 5). However, among the variants, the results are different from what was found with the velocity citerion, because the velocity-based variant gives here the best gain (i.e., the highest diminution of the collisions).
- Finally, the average itinerary length remains identical whatever model variant is used.

In summary, these results show that the introduction of the following mode in complement to the SFM allows some improvements in the simulation fluidity. We explain this result by a higher homogeneity in the group flow, regarding its direction and velocity, when the agents can activate the following mode to face high density.

4.2 Threshold Values Evaluation

In these second experiments, in the same conditions as the first ones about the simulation environment, we have compared different values of the thresholds: $s_p^N \in \{2,3,4\}$ pedestrians, $s_p^d \in \{20,30,60\}^\circ$, and $s_p^v \in \{0.4,0.5,0.6\}$ $m.s^{-1}$. The combination of the different values together with each variant of the model produces 81 possibilities, which have been evaluated using the velocity and collision number criteria used in the first experiments. We will not give here all the results, but only the most significant of them that concern the direction variant.

The standard deviation in the velocity remains similar with the different threshold values. We can notice however that the lowest deviations, i.e. the weakest difference of speeds between agents, are given for the values $s_p^d = 60^\circ$ and $s_p^v = 0.5$ $m.s^{-1}$, which means this combination produces a more homogeneous flow.

Regarding the number of collisions, the results show improvements compared to the SFM, as in the first experiments. Excepted that the collisions rise when s_p^N is low and s_p^d and s_p^v are high, especially with the combination $s_p^N = 2$, $s_p^d = 60$ and $s_p^v = 0.6$. Such a situation makes the conditions to activate the following mode easier to be validated, and thus a higher amount of agents decide to switch to the following mode. Our explanation, at this step of the study, for the increase in the amount of collisions, is that the following mode tends to decrease the velocity, and thus can lead to more congested situations, with more collisions.

5 CONCLUSIONS

We have proposed a following mode to be included in a perception-oriented hierarchical architecture to model and simulate the pedestrian behavior. The final aim is to simulate heterogeneous pedestrian population, including pedestrians who follow and other ones who avoid. The proposition enables the pedestrian agent to activate the following mode depending on the situation, on the base of its internal state and its perception. In addition to the positions of the others like in Helbing's model, the proposed model allows to take into account other criteria, i.e. neighborhood density, current direction and velocity. First experiments were realized with three variants of the model concerning the selection of the leader for the following mode. Evaluations made with performance and quality indicators (average velocity and number of collisions) seem promising. They show that, in crowded environment, the model allows to improve the flow with a higher average velocity while lowering the number of collisions.

A lot of work remains to be done. We have to carry out new experiments in different environments, to confirm and better understand the effects of the model on the flow, and the parameterization of the distances. Additional indicators could help us to characterize the three variants of the model. Moreover, we would like to be able to reproduce the stop-and-go phases simulated in Lemercier's study about waiting files (Lemercier et al., 2011). Further works are currently done (Ketenci et al., 2010), which we intend to integrate as parts of the pedestrian global model.

ACKNOWLEDGEMENTS

This work forms a part of the TerraDynamica project, with funding from the French *Fonds Unique Interministériel* (FUI).

REFERENCES

Allen, T. M., Lunenfeld, H., and Alexander, G. (1971). Driver information needs. *Highway Research Board*, 36:102–115.

Bourgois, L., Saunier, J., and Auberlet, J.-M. (2012). Towards contextual goal-oriented perception for pedestrian simulation. In Filipe, J. and Fred, A. L. N., editors, *ICAART (2)*, pages 197–202. SciTePress.

Fruin, J. (1971). *Pedestrian planning and design*. Metropolitan Association of Urban Designers and Environmental Planners.

Hanon, D., Grislin-Le Strugeon, E., and Mandiau, R. (2003). A behavior based architecture for the control of virtual pedestrians. In *The 2nd Int. Conf. on Comp. Intell., Robotics and Aut. Syst. CIRAS*, pages 125–132.

Helbing, D. and Molnar, P. (1995). Social force model for pedestrian dynamics. *Physical Review E*, 51:4282–4286.

Hoogendoorn, S. P. and Bovy, P. (2000). Gas-kinetic modeling and simulation of pedestrian flows. *Transportation Research Record*, pages 28–36.

Hoogendoorn, S. P. and Daamen, W. (2005). Pedestrian behavior at bottlenecks. *J. Transp. Sc.*

Huat, L., Ma'Some, D., and Shankar, R. (2005). Revised walkway capacity using platoon flows. In *Eastern Asia Society for Transportation Studies*, volume 5, pages 996–1008.

Ketenci, U., Brémond, R., Auberlet, J., and Grislin-Le Strugeon, E. (2010). Bounded active perception. In *8th European Workshop on Multi-Agent Systems EUMAS*.

Lemercier, S., Jelic, A., Hua, J., Fehrenbach, J., Degond, P., Appert-Rolland, C., Donikian, S., and Pettre, J. (2011). Un modèle de suivi réaliste pour la simulation de foules. *Revue Electronique Francophone d'Informatique Graphique*, 5(2).

Moulin, B. and Larochelle, B. (2010). Crowdmags, multi-agent geo-simulation of the interactions of a crowd and control forces. *Modelling, Simulation and Identification*, pages 213–237.

Moussaid, M., Perozo, N., Garnier, S., Helbing, D., and Theraulaz, G. (2010). The walking behaviour of pedestrian social groups and its impact on crowd dynamics. *PLoS ONE*.

Qiu, F. and Hu, X. (2010). Modeling group structures in pedestrian crowd simulation. *Simulation Modelling Practice and Theory*, 18(2):190–205.

Reynolds, C. (1987). Flocks, herds, and schools: A distributed behavioral model. *Computer Graphics*, 21(4):25–34.

Schadschneider, A., Kirchner, A., and Nishinari, K. (2002). Ca approach to collective phenomena in pedestrian dynamics. In *Cellular Automata*, volume 2493 of *LNCS*, pages 239–248. Springer.

Teknomo, K. (2009). Application of microscopic pedestrian simulation model. *Transp. Res., Part F*, 9:15–27.