Behavioral dynamics for pedestrians

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Abstract

The objective of this paper is to identify the behavioral issues arising in the context of pedestrian dynamics, analyze how they have been addressed in the literature, and propose some potential research tracks. We particularly focus on an application in the context of automatic video surveillance, and present first ideas for the design of a pedestrian simulator.

Keywords

Pedestrian, Simulation, Image analysis, International Conference on Travel Behaviour Research, IATBR

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1. Introduction

The development of Intelligent Transportation Systems has triggered important research activities in the context of behavioral dynamics. Several new models (driving and travel behavior models), new simulators (traffic simulators, driving simulators) and new integrated systems to manage various elements of ITS, have been proposed in the past decade (see Mahmassani, 1996, Golledge, 2002). With regards to pedestrians, the focus of ITS has mainly been on safety issues (see, for example, Fuerstenberg *et al.*, 2002), and modeling pedestrian movements in detail has rarely been considered.

Pedestrian simulation has received a more important attention in the context of crowd evacuation management, and panic situation analysis. In 2001, the first international conference on Pedestrian and Evacuation Dynamics took place in Duisburg, Germany (Schreckenberg and Sharma, 2002), showing the growing interest in pedestrian simulation in the scientific community. The objective of this paper is to identify the behavioral issues arising in the context of pedestrian dynamics, analyze how they have been addressed in the literature, and propose (when appropriate) some potential research tracks. We particularly focus on an application in the context of automatic video surveillance.

The ability of predicting the movements of pedestrians is valuable in many contexts. The panic situation analysis is probably the one which has motivated the large majority of research activities in the field (e.g. Helbing *et al.*, 2000, Klüpfel *et al.*, 2000, Helbing *et al.*, 2002). However, it is a specific situation. Not only the range of applications is small, but also the behavior of individuals is dictated by a unique objective (save their own life) and may become irrational (Schultz, 1964, Quarantelli, 2001). Capturing the behavior of pedestrians in "normal" situations is also important in architecture (Okazaki, 1979), urban planning (Jiang, 1999), land use (Parker *et al.*, forthcoming), marketing (Borgers and Timmermans, 1986b) or traffic operations (Nagel, in progress).

This paper is motivated by new research projects conducted at Ecole Polytechnique Fédérale de Lausanne (EPFL) in the context of video surveillance, image analysis and objects tracking, where the objective is to be able to trigger alarms when unusual events are detected in the video sequence, in real-time. Current tracking methods can be divided into two main classes. Bottom-up approaches use image processing techniques to try to separate the background image from the moving objects. Standard morphological operations are performed to reduce the noise and increase the unity of connected components of the objects. After the connected objects are detected, some statistical descriptors are calculated: mean, variance, relative smoothness, skewness, energy, entropy (on the colored images) and area, perimeter (for binarized images). Objects that are too small are considered as noise and deleted. Matching methods are then used to "track" each object from one frame to another. Top-down approaches generate hypotheses and test them using information from the image. A description of the target region is given in term of some features (histograms are commonly used), and hypotheses can be statistically tested . We refer the interested reader to D. Koller and Malik (1994), Isard and Blake (1996), D. Comaniciu and Meer (2000) and Isard and MacCormick (2001) for more information about tracking.

More and more experts (Thiran and Kunt, 2003) recognize that this class of methods is reaching its limits. A promising new track of research is the combination of tracking methods with mathematical models of the content of the image. In this spirit, the objective of our research projects is to combine state of the art tracking tools with a model simulating the content of the image, that is pedestrian movements. The main idea is summarized in Figure 1. The tracking module segments the video image and identifies locations and trajectories of objects (typically, human beings), used to calibrate the models. The role of the simulator is to anticipate how those objects will continue to move in the near future within the scene and therefore, within the image. The predicted location of the objects is then a robust reference for the tracking module.

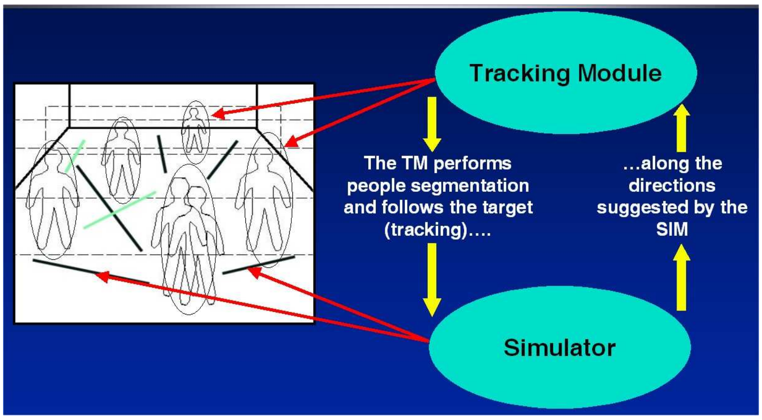

Figure 1: Interaction between the image analysis module and the simulator

Designing a pedestrian simulation tool and pedestrian behavior models in this context generate interesting issues which have not necessarily been addressed in the literature. In this paper, we present our concept for the design of such a tool, in the light of the existing literature. We have adopted an approach where various types of behavior are modeled.

A major challenge is the actual calibration of the models. Indeed, we have noticed that few models presented in the literature have been calibrated and validated on real data. Data collection for pedestrian dynamics is indeed particularly difficult. Even calibrating a speed-concentration relationship is not straightforward (AlGadhi *et al.*, 2002). We have adopted an approach where discrete choice models are combined in a simulator, capturing various choices made by a pedestrian during her journey. Each model which is presented below is designed to be calibrated independently of the others from real data. The intention is to use data produced by existing tracking algorithms to identify trajectories within a scene from video recordings, similarly to Teknomo *et al.* (2000) and Teknomo *et al.* (2001b).

The modeling elements and simulator design presented below are prospective. A full implementation of the simulator, with calibration and validation of the models is necessary to assess the relevance of those ideas. The sole objective of this paper is to trigger ideas and discussions during the IATBR conference.

2. Methodological approaches for behavioral dynamics

Several methodological approaches can be considered to capture behavioral dynamics in general and pedestrian dynamics in particular. We briefly discuss some of them.

System dynamics are based on equations describing the evolution of a system over time. Discrete time models have the following form

$$x_{t+1} = f(x_t, \beta) \tag{1}$$

where x_t is a vector of state variables at time t, and β are model parameters. Continuous time models are captured by differential equations, such as

$$\frac{dx}{dt} = f(x(t), \beta) \tag{2}$$

where the vector of state variables $x(t)$ is a continuous function of time. This has been used for pedestrian simulation in the literature (Helbing and Molnár, 1995, Teknomo *et al.*, 2001a). However, we believe that complex behavioral rules and behavioral heterogeneity are difficult to capture with such models. Moreover, in most practical cases, there is no analytical solution to (1) or (2). Consequently, we have decided not to adopt this approach.

While system dynamics are time-based, *queuing models* are event-based, in the sense that they compute the state of the system for each event in a predefined agenda. The system is composed of several servers organized within a network. Each server processes items at a given rate. Items not yet processed are accumulated in queues associated with each server. The arrival of items and the service time for each server is modeled by a stochastic process. Queuing models are not appropriate to capture pedestrian dynamics. The concept of servers and the network organization do not correspond to a tangible reality.

Game theory mimics the behavior of players, adopting a strategy knowing the strategy adopted by other players. The outcome of a game is characterized by a payoff matrix. The main focus of game theory is to identify and analyze equilibrium situations, such that no player can improve her own payoff by unilaterally changing her strategy. The approach is relevant in the context of pedestrian simulation, where the behavior in a crowd strongly depends on the behavior of other persons in the crowd. Because of the large number of "players" and the difficulty to identify an appropriate payoff matrix, we have decided to postpone the use of game theory for pedestrian simulation for future research projects.

Cellular automata allow for a time-based simulation approach, where the state of the system is represented by a regular grid composed of cells (see Toffoli and Margolus, 1987 for an introduction). Each cell can be in one of a few states (typically two, 0 or 1). At each time step, the state of each cell is updated based on its previous state and the previous state of its immediate neighbors. Therefore, it is designed for situations with local interactions. Cellular automata have been successful in the context of traffic simulation (see, for instance, Rickert *et al.*, 1996). It is also appealing to model pedestrian behavior, and has been adopted by several authors (see, for example, Dijkstra *et al.*, 2000, Blue and Adler, 2001, Schadschneider *et al.*, 2002 and Yang *et al.*, 2002). We have decided that this approach is not appropriate in our context, due to the fixed regularity of the grid, the homogeneity of the rules and the limited number of states of each cells.

We conclude this section with the two main methodological approaches that we have adopted: *agent-based simulation* and *discrete choice models*. An agent is an entity with its own behavior within the simulator. Developed in the context of artificial intelligence (see, for instance, Ferber, 1998), agent-based simulation has been widely used in the context of traffic simulation (Yang and Koutsopoulos, 1997, Mahmassani *et al.*, 1993, Barceló and Ferrer, 1997, Ben-Akiva *et al.*, 2002). It provides a great deal of flexibility, as the behavior of each element in the system can be modeled independently, and complex interactions can be captured. In our context, each pedestrian is an "agent". The behavior of each agent can be modeled as a sequence of specific choices, such as the choice of the destination, the choice of the itinerary, the choice of an overall direction, or the choice of where to put the next step. Discrete choice models in general, and random utility models in particular are disaggregate behavioral models designed to forecast the behavior of individuals in choice situations (Ben-Akiva and Lerman, 1985). They assume that each alternative in a choice experiment can be associated with a value, called utility. The alternative with the highest utility is selected. The utility of each alternative is a latent concept which is modeled as a random variable depending on the attributes of the alternative and the socio-economic characteristics of the decision-maker. Several probability models describing the choice process have been proposed in the literature, each corresponding to a specific assumption about the distribution of the random variable.

3. Modeling elements

Pedestrian and crowd dynamics have been studied, from an empirical point of view, for some decades using time-lapse films, photographs and direct observations. These initial efforts have brought a good empirical knowledge about the different behaviors of individuals in several kinds of environments and situations. Based on this empirical knowledge, we identify the following most important *modeling elements*.

3.1 Agents

The complexity of pedestrian behavior comes from the presence of collective behavioral patterns (as clustering, lanes and queues) evolving from the interactions among a large number of individuals. This empirical evidence leads to consider two different approaches: pedestrians as a flow and pedestrians as a set of individuals or agents. In the first case, the crowd is described with fluid-like properties, describing how density and velocity change over time using partial differential equations (Navier-Stokes or Boltzmann-like equations). This approach is based on some analogies observed at medium and high densities. For example, the footprints of pedestrians in snow look similar to streamlines of fluids or, again, the streams of pedestrians through standing crowds are analogous to river beds (Helbing *et al.*, 2002).

Nevertheless in these analogies, the fluid-dynamic equation is difficult and not flexible. As a consequence, current research focuses on the *pedestrian as a set of individuals* paradigm. This means **microscopic** models, where collective phenomena emerge from the complex interactions between many individuals (self-organizing effects). One example of such models is the *social forces* model of Helbing and Molnár (1995) where an individual is subject to long-ranged forces and his dynamics follow the equation of motion, similar to Newtonian mechanics. Another example is the Cellular Automaton (CA) model. In this case the local movements of the pedestrian are modeled with a *matrix of preferences* which contains the probabilities for a move, related to the preferred walking direction and speed, toward the adjacent directions. Schadschneider (2002) introduces the interesting concept of *floor field* to model the long-ranged forces. This field has its own dynamic (diffusion and decay), is modified by pedestrians and in turn modifies the matrix of preferences, simulating interactions between individuals and the geometry of the system. All the agent-based models are also microscopic models and are based on some elementary form of intelligence for each agent (attempts to provide a *vision* and/or *cognition* capabilities). Simple behavioral rules are implemented (turning directions, obstacle avoidance) in order to reproduce more complex collective phenomena (Penn and Turner, 2002).

Our model belongs to the microscopic model category, where pedestrians/agents behave in their environment by making a sequence of decisions.

3.2 Space

The representation of the physical space plays a central role in the simulation. The Cellular Automata model (Schadschneider, 2002) uses a discrete structure of space. A grid of 40x40 cm^2 cells is overlapped to the area available for pedestrians. This is the typical space for each individual in a dense crowd. The same grid structure is used by Kessel *et al.* (2002). Helbing *et al.* (2002), in their social force model, use the equation of motion to describe the change of location $x_i(t)$ of the pedestrian *i*, assuming a continuous treatment of space, similarly to the multi-layer utility maximization approach proposed by Hoogendoorn *et al.* (2002). In all these models the pedestrian is seen as a point or a particle in a 2D environment. With the recent development in rendering techniques and Virtual Reality simulations, other models are based on a 3D representation. In the agent-based approaches, the agent moves through a virtual environment where the movements can be discrete or continuous (Thalmann and Bandi, 1998, Penn and Turner, 2002).

A completely different approach is proposed by Borgers and Timmermans (1986b). They use a network representation, where each node corresponds to a city-center entry point or a departure point and each link denotes a different shopping street. In this case, the network topology represents the walkable space and any movement occurs along the links between two consecutive nodes.

The space model is directly connected with the concept of visual field. Indeed, pedestrians are influenced by what they actually see. More precisely, the complex cognitive mapping and learning process in a human being, find their first source of inputs from the images of the space around. Some attempts of explicit modeling have been done in the robotics community (Bachelder and Waxman, 1994), who simulate the hippocampal cognition process with a really high computational cost. Important studies on the interactions between pedestrians and the space are made by Timmermans group (Essyx tool), while a pedestrian simulator that tries to reproduce the visual field is EVAS (Penn and Turner, 2002). The EVAS approach is based on an evolution of the *Space Syntax* theory (B.Hillier and J.Hanson, 1984 and Hillier *et al.*, 1993): the Visibility Graph Analysis (VGA). The configuration of the space seems to be one of the first sources in the variance of human behavioral patterns. The VGA states that, given a grid of points that covers the space layout, it is possible to create a graph, the *visibility graph*. Each grid's point represents a node and two nodes are connected if and only if they are mutually visible (another possibility is *one-depth* visibility that is, visible by means of an intermediate node). From the graph, it is possible to calculate some features of the space that are important for pedestrian way-finding. The first of these coefficients is the *Neighborhood size* N_i defined as the set of directly visible vertices:

$$N_i = \{v_j : e_{ij} \in E\} \tag{3}$$

where N_i is the neighborhood of location v_i, e_{ij} is the link between nodes v_i and v_j and E is the set of all links in the graph. The neighborhood size value is proportional to the visible area and its plot draws contours of equal viewable areas across the space (Turner *et al.*, 2001). Another important measure is the *clustering coefficient* C_i for the neighborhood N_i (of size k_i) of location v_i:

$$C_i = \frac{|\{e_{jk} : v_j, v_k \in N_i \wedge e_{jk} \in E\}|}{k_i(k_i - 1)} \tag{4}$$

Practically is the number of edges between all the vertices in the neighborhood of vertex v_i divided by the total number of possible connections with that neighborhood size. It can be seen also as a measure of the inter-visible space within the visibility neighborhood of a point. Again if we think about a pedestrian in position v_i, the C_i values give a measure of the potential to form groups or to interact (Turner *et al.*, 2001). Conroy (2001) have further shown that in multi-directional visual field areas, as junctions, there is a strong correspondence with the stopping behavior of people (thinking about a new direction). Many other features can be extracted from the graph, as the mean shortest path length, given to the pedestrian a rude form of cognition or memory.

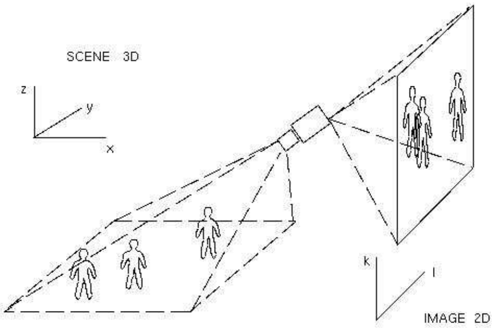

Figure 2: Correspondence between the 3D simulator environment and the 2D image

Obstacles and attractors must be also modeled. Fixed obstacles are represented by regions that no pedestrian can access. Moving obstacles are (groups of) other pedestrians occupying some space which is consequently not anymore available. Attractors are useful areas with particular meaning for the individuals. Examples of attractors can be the shopping windows or areas becoming interesting because of the presence of painters or musicians. Helbing *et al.* (2002), in their social force model, take into account time-dependent attractive interactions. They use social forces with an interaction range longer and a strength parameter smaller compared with repulsive interactions. So, practically, they define attractors as long-range forces.

Finally, origin and destination areas, where pedestrians enter and exit the system must be defined. Those could be doors, elevators, stairs, and of course the boundaries of the modeled area.

In our context of video analysis, we prefer to adopt a 3D approach. Indeed, several cameras can observe the same area. The 3D scene in the simulator can be projected for each of the camera in order to compare the simulation with the actual image, as illustrated in Figure 2.

In the automatic video surveillance application context, if there is a one-to-one correspondence between the simulator horizontal plane and the horizontal plane as projection of the image plane (see Figure 2), the same mapping of the space can be used by both the simulator and the tracking module. This could create a good connection point between the two modules, providing the tracking algorithm with more *intelligence* (the most viewable and accessible areas are also the areas with the highest probability to be crowded, so the tracker should be "more attentive" in these zones, projected back on the image plane).

The idea that stems from the visibility graph analysis (VGA) and space syntax theory in general is to provide the pedestrian with some kind of *vision*. The ability to "see" is a key attribute of the decision-maker. Of course, in real situations, the *lines-of-sight* of the visual field are influenced by the presence of other pedestrians and obstacles. What we have in mind is to use VGA as a starting point to model all the static information about the space. This would provide the pedestrian with a knowledge about the visibility and accessibility of the different places in the environment. The VGA coefficients can be easily used in a Discrete Choice Model framework as attributes of alternatives taken inside the visual field. They represent a pre-processing step and are computed just one time. A second step would be to modify the lines of sight using the data coming from the tracking module, namely information about the presence of group of people representing a visual obstacle.

We adopt a *dynamic individual-based spatial discretization*. Contrarily to the CA approach where the discretization is static, the space discretization we propose varies with time, with the behavior that must be captured, and is different for each agent in the system. Namely, we consider three space representations:

1. A network-based representation is designed to capture strategic decisions made by the pedestrian even before being in the scene, like destination choice and route choice (see Figure 3). The network design is derived from the concept of *visibility graph* described above.

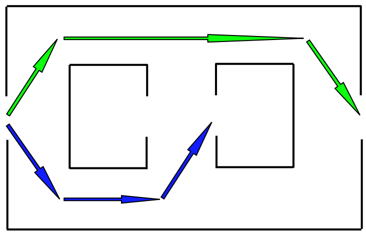

Figure 3: Network-based representation

2. A radial and individual-specific discretization of space is designed to capture decisions about the walk direction (see Figure 4). The space is divided into sectors originating at the individual locations. The central sector is oriented with the current direction of the pedestrian. The number and angles associated to these sectors are designed from the concept of *visual field* discussed above.

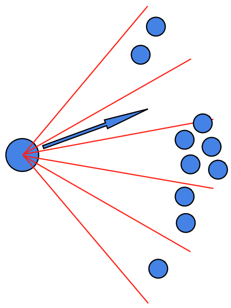

Figure 4: Radial discretization

3. A grid and individual-specific discretization of space is designed to capture decisions about the next step, considering local interactions (see Figure 5). As for the radial discretization, the grid is aligned with the current direction of the pedestrian. The size of the cells in the grid is typically 50 to 80 centimeters, that is the magnitude of a footstep. In this case, at most one pedestrian can physically occupy it at any point in time. However, for large scale applications, we may need to increase the size of the cells for efficiency purposes.

4. Behavior

Adopting an agent-based approach, we consider several decisions taken by pedestrians and the associated behavioral models.

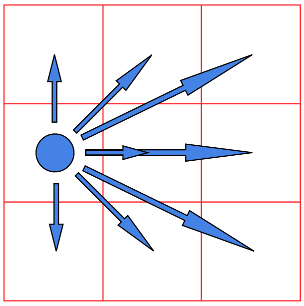

Figure 5: Grid discretization

4.1 Destination choice

The destination choice problem is tricky in the context of pedestrian simulation. Indeed, some individuals may not have a destination at all if, for instance, they are walking around waiting for a bus. In shopping areas, the destination may change rapidly depending on the environment or on the attractors (see Whynes *et al.*, 1996, Dellaert *et al.*, 1998).

Borgers and Timmermans (1986b) propose a simulation of pedestrians in the shopping streets of the city centers. The model is a Monte Carlo simulation which implies that the behavior of each individual is simulated by a series of draws of random numbers from successive probability distributions. In their work, the authors build different sub-models related to the number of goods bought by pedestrians, in which retail sector, in which link of the urban network (the link is the shopping street). As an example, we report the link-choice model:

$$p^g_{nl} = \frac{(\sum_{m\in l} F^g_m)^\alpha \exp\left(-\beta \min\left[\sum_{l''\in r} d_{l''}\right]\right)}{\sum_{l'=1}^{L}\{(\sum_{m\in l'} F^g_m)^\alpha \exp\left(-\beta \min[\sum_{l''\in r} d_{l''}]\right)\}} \tag{5}$$

where p^g_{nl} is the probability that a good in retail sector g will be bought at link l providing that the pedestrian departed from city entry point n, F^g_m is the total amount of floorspace in retail sector g at destination $m(m = 1, 2, ..., M)$, $\min\left[\sum_{l''\in r} d_{l''}\right]$ is the distance associated with the shortest route from city entry point n to link l, and α,β are parameters to be estimated.

Another important work, from a procedural point of view, is that of Hoogendoorn *et al.* (2002). The principle is that an individual chooses her destination based on the activities she wants to perform. Hence, the problem of destination selection becomes a problem of activity planning and scheduling as well as the activity area choice. However, in such a model, the authors consider the destinations of the pedestrians to be known. The activity sets, travel purposes and all the events and decisions causing the pedestrian to arrive at the walking facility are not considered or are assumed to be known a-priori. The most important contribution of this work is the assumption that all the decision-making process of pedestrians is distributed along a hierarchical structure. At the high (strategical), medium (tactical) and low (operational) level, the pedestrian is involved in a *destination selection* process. The strategical selection depends on the activity scheduling and trip purposes. The tactical selection comes from *event response* and *obstacle avoidance* and the operational selection is based on the interactions with the other pedestrians.

Finally, Kopp (1999) uses in the EVACSIM simulator the so called *Primary/Secondary* destination selection. A shortest path algorithm, using a sub-goal system, was developed for this simulator to allow people to effectively navigate around obstacles. If a person's path to an exit destination is blocked (checked with a line intersection test), the person finds a sub-goal that is in a line-of-sight with the person. If multiple sub-goals are in a line-of-sight, the person chooses the one that will lead to the shortest path to the exit destination. This approach to model the *destination selection* is local and captures an obstacle avoidance behavioral pattern. It doesn't deal with any "high level" decision process as for example trip purpose or activity-based scheme. Moreover, EVACSIM is mainly oriented to evacuation situations, where the pedestrians have one or multiple exits and their behavior is essentially an event response pattern (for example fire in a building).

In our context of video image analysis, we assume that the destination of each individual is given a priori, and corresponds to one of the destination areas defined in Section 3.2. Intermediate destinations, or goals, can be modeled based on the concept of visual field (that is, the next visible goal to reach on the path to the final destination), and are associated with the displacement model, not the destination model. The possible attractors in an environment (musicians, shops and the like) will be modeled as intermediate goals as well, not as destinations.

4.2 Route Choice

Borgers and Timmermans (1986a) addresses the route choice problem as an utility maximization problem. The *objective characteristics* X_{lk} of the link l are transformed into subjective perceptions or evaluations by means of a functional relationship f_k:

$$x_{lk} = f_k\{X_{lk}\}, k = 1, 2, ..., K. \tag{6}$$

After that, the *subjective utility* $U(l)$ is obtained as an algebraic combination of the subjective values:

$$U(l) = h(x_{lk}), k = 1, 2, ..., K. \tag{7}$$

Likewise, the route's utility equals:

$$U(r) = h'(U(l); d_r), l \in r \tag{8}$$

where h' is another algebraic function and d_r is the total subjective distance associated with route r. The pedestrian will choose the route that will maximizes his subjective utility.

Hoogendoorn *et al.* (2002) addresses the problem of route choice in the *tactical level* of their hierarchical model. After the activity scheduling (which activities and in which order are performed), the authors consider the combined route choice and activity area choice of a pedestrian. The principle is always the utility maximization (more precisely the *expected disutility minimization*) taking into account different route attributes such as travel time, distance traveled, safety, comfort, etc. They do not use a discrete choice framework; the number of choice options is infinite in continuous time and space. We show, as an example, the equation used to describe the expected cost C_i:

$$C_i(T_i, v_{[t,T_i)}|T_{i-1}, x(T_{i-1})) = E\left[\int_t^{T_i} L(\tau, x(\tau), v(\tau))\, d\tau + \phi(T_i, x(T_i))\right] \tag{9}$$

The time interval $[t, T_i)$ denotes the interval between the current time and the arrival time at an activity area while $v[t, T_i)$ is the velocity path. The *running cost* $L(\tau, x(\tau), v(\tau))$ shows the costs incurred during the time interval $[\tau, \tau + d\tau)$ where $x(\tau)$ is the location and $v(\tau)$ is the applied velocity to change the position. The *terminal cost* $\phi(T_i, x(T_i))$ reflects the cost due to ending up at position $x(T_i)$ at the terminal time T_i. The terminal cost represents the penalty ϕ_i for not having arrived in time at any of the

activity areas. The running cost is related to the different contributions of the different route attributes (discomfort, walking at certain speed, expected number of pedestrian interactions etc.)
Blue and Adler (2001) analyse the problem from a *self-organizing* point of view. They use a CA model, with a limited rule-set for the pedestrian behavior and look at the emergent collective behaviors. Their route-choice is lane-based. They show how unidirectional, bi-directional, cross-directional and 4-directional pedestrian flows emerge from CA simulations. The model centers on a two-stage parallel update process whereby lane assignment and forward motions change the positions of all pedestrians in two parallel update stages in each time step. They assume that only pedestrians in the immediate neighborhood affect the movement of a pedestrian. We believe that this assumption is valid only at the operational level in a hierarchical model (the local interactions among pedestrians).

There is a distinction between the individuals who know their destinations and the others who do not have a precise destination. All the models seen until now, refer to the first category. We could talk about *explorers* referring to people who do not have a specific destination. It is clear that, in this case, the behavioral patterns are different and other parameters become important. Penn and Turner (2002), in their EVAS simulator (agent-based), address this kind of population. The agent takes a decision about her destination and chooses the route every three steps, basing the decision process on the simulated visual field. The direction is chosen randomly inside the visual field. We think that this is a limitation and is applicable to the only exploratory pattern. It would be interesting to apply these concepts in a discrete choice model framework, using the visual field as a source of exogenous information and mixing it with endogenous parameters.

We conclude this section saying that the idea to address the destination and/or route choice problems in a pedestrian behavior context, stems from previous research activities, namely in the Intelligent Transportation System context. Among the route choice literature, we refer the reader to Ben-Akiva *et al.* (1984), Charlesworth and Gunawan (1987), Bovy and Stern (1990), Cascetta *et al.* (1992), Ben-Akiva and Bierlaire (1999) and Ramming (2001). As already mentioned in the introduction, several new models capturing driver behavior and traveler behavior, as well as traffic simulators have been extended to the pedestrian behavior and way-finding problems (Muramatsu *et al.*, 1999).

In our approach, we adopt a route choice model based on the network based representation of space described in Section 3.2. We assume that the choice of the route is a strategic decision, made based on historical knowledge of the topology of the environment.

4.3 Speed and collision avoidance

In an empty space, the destination and the path are almost sufficient to reproduce the journey of a given pedestrian. Almost, because an average speed must be assumed, and small random deviations from the given path must be allowed for the sake of realism. When the environment is crowed and contains obstacles, the direction and the speed of the pedestrian may be significantly affected.

In most models in the literature, the important parameters influencing the behavior are the speed (concepts of desired speed and speed regimes) and the density of individuals to define the collision avoidance pattern. In the social force model, the desire to adapt the actual velocity $v_i(t)$ to the desired speed v_t^0 within a certain "relaxation time" τ_i is reflected by the *acceleration term* $[v_i^0 e_i^0 - v_i(t)]/\tau_i$. The contribution $v_i^0 e_i^0/\tau_i$ is interpreted as a *driving term* and $-v_i(t)/\tau_i$ as a *friction term*. The CA model addresses the problem using the dynamic of the *floor field*. So, the movement of a pedestrian is considered as the movement of a particle that crosses a field with its own dynamic (diffusion and decay). In the lane-based approach, Blue and Adler (2002) design the model to account for variations in walking speeds observed in the real world. Each time step is one second and they consider walking speed varying among pedestrians, using distribution of walking speed with a cell size of 0.21m^2:

1. *fast walkers*: maximum speed of 4 cells per time step (about 1.8m per time step);
2. *standard walkers*: maximum of 3 cells per time step (1.3m per time step);
3. *slow walkers*: maximum of 2 cells per time step (0.85m per time step).

In their experiments, they use a population composed of 5% of fast, 90% of standard and 5% of slow walkers. In the multi-layer utility maximization model, Hoogendoorn *et al.* (2002) define the kinematics of the pedestrian as follows:

$$dx = vdt + \sigma dw \tag{10}$$

where $v = v(\tau)$ is the velocity vector for $\tau > t$. The term w is a Wiener process and denotes the *uncertainty in the expected traffic conditions* and its effects on the pedestrian's kinematics. The speed of the individual is limited by the physical conditions and by the other individuals. There is a set of *admissible velocities* defined as

$$V_a(t, x) = \{v : \|v\| \leq v_0(t, x)\} \subset \mathbb{R}^2 \tag{11}$$

The t and x dependence describes the changing of the maximum speed stemming from the change in flow conditions as well as differences in maximum speed between different parts of the walking infrastructure. Last, but not least, the maximum speed of a specific pedestrian also depends on the individual's characteristics (age, gender, trip-purposes, luggage etc.)

The *collision avoidance* pattern stems automatically from a combination of the velocity vector of the other pedestrians and the density parameter. In microscopic models, an individual tries to keep a minimum distance from the others ("territorial effect"). In the social force model, this pattern is described by repulsive social forces:

$$\mathbf{f}_{ij} = A_i \exp\left[(r_{ij} - d_{ij})/B_i\right]\mathbf{n}_{ij}(\lambda_i + (1 - \lambda_i)\frac{1 + \cos\varphi_{ij}}{2}) \tag{12}$$

where A_i is the interaction strength, B_i the range of the repulsive interaction, d_{ij} the distance between pedestrians i and j, r_{ij} the sum of the radii, $\mathbf{n}_{ij}$ the vector pointing from i to j, the angle φ_{ij} denotes the angle between the direction of motion and the direction of the object exerting the repulsive force. Finally, the parameter λ_i takes into account the fact that the situation in front of a pedestrian has a larger impact than things happening behind.

We believe that most models proposed in the literature are somehow myopic. They attempt to avoid collisions between pedestrians at local level describing the so called collision avoidance and passing behavior patterns. These patterns are reproduced drawing a physical parallel, using repulsion forces and mutually exclusive positions in the space grids (as in CA models). These kinds of models may lead to an unrealistic behavior as reported in Figure 6, where path a results from a pure collision avoidance model with the propension to go around an obstacle, following its boundaries. This behavior is a characteristic of such models where the agent has no visual field. They are myopic in the sense that they use the same local space model for all kind of interactions (collision with other pedestrians and obstacle avoidance). We aim to solve this problem using two different structures of the space (see Section 3.2). As a consequence, trajectory b should be preferred, as it originates from a *vision capability* of the agent. We intentionally focus the attention on this fact to underline the importance of the visual field as a modeling element.

Instead of using models inspired from analogies with physics, basically dealing with human beings as particles or some other elementary units, we propose to use behavioral models. We believe that the mathematical framework of discrete choice models allows to better reproduce behavioral patterns than the physical models.

The models we propose are consistent with the dynamic individual-based spatial discretization presented in Section 3.2, and we refer to them as the long-range, mid-range and short-range models. As discussed

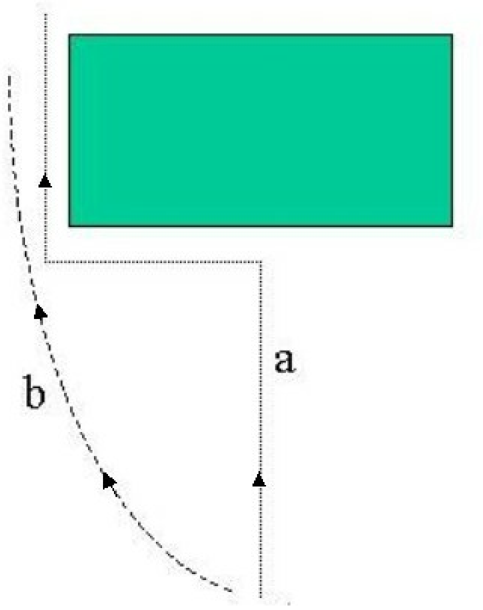

Figure 6: The trajectory without a visual field (a); the trajectory with visual field (b)

in Section 4.2, the long-range model is a route choice model based on a network-based representation of space.

The mid-range model is designed to better capture the type of behavior described in Figure 6, and is based on the radial space representation illustrated by Figure 4. It is a random utility model where each alternative is a combination of a sector in the radial representation and a speed regime (typically normal, slow, fast). The utility of each alternative is affected namely by the presence of fixed obstacles in the sector (group of static people, columns, etc.), by the visibility of the pedestrian in its current position, by the spatial layout (building walls), the deviation from the a priori path that the agent wishes to follow, the density of the crowd in the sector and the position and speed of individuals in the sector. If a leader has been identified (see next section), her movements are important attributes of the utility function. Other attributes, like the number of directional changes already done may also be considered. Due to the obvious spatial correlation across alternatives, models like the Cross-Nested Logit model (Small, 1987; Vovsha, 1997; Bierlaire, 2001; Wen and Koppelman, 2001) or the Network GEV model (Daly, 2001; Bierlaire, 2002) will be calibrated.

The short-range model is consistent with the grid discretization of space illustrated by Figure 5. It is a random utility model where each alternative is a cell of the grid. A cell is an available alternative if it is reachable within the next time interval given the speed of the walker, and if it contains no obstacle. For the current pedestrian, the utility of each cell depends on its distance to the pedestrian, on the behavior of the near walkers (if, given their trajectories, they are going to be on the cell in the near future). Namely, if a leader has been identified, her movements (position and speed) are important attributes of the utility function. Again, the spatial correlation among the alternatives must be taken into account.

An important advantage of the discrete choice framework is its ability to segment the population of pedestrians, defining different decision-maker characteristics (trip purpose, age, mobility, “aggressiveness” etc.) So, different individuals will choose a different alternative even when facing the same choice set. This property gives us the possibility to better reproduce the variance in people’s movements.

4.4 Crowd effects

One of the first approaches to describe the crowd effect was that of Reynolds (1987), the so called *leader-follower* pattern. One or more individuals follow another moving individual designated as the leader. Generally the followers want to stay near the leader, without crowding the leader, and taking care to stay out of the leader's way (in case they happen to find themselves in front of the leader). In addition, if there is more than one follower, they want to avoid bumping into each other. The implementation of leader following relies on *arrival behavior*, a desire to move toward a point, slowing down as it draws near. The arrival target is a point offset slightly behind the leader. (The offset distance may optionally increase with speed). If a follower finds herself in a rectangular region in front of the leader, she will steer laterally away from the leader's path before resuming arrival behavior.

In the social force model of Helbing *et al.* (2002), physical interaction forces come into play when pedestrians get so close to each other that they have physical contact. This is mainly the case in panic situations but also as a reaction to an event. The authors assume a *body force* $k(r_{ij}-d_{ij})\mathbf{n}_{ij}$ counteracting body compression and a *sliding friction force* $k(r_{ij}-d_{ij})\Delta v^t_{ij}\mathbf{t}_{ij}$ impeding relative tangential motion. The model for this effect comes from the granular interaction formula:

$$\mathbf{f}^{ph}_{ij}(t) = k\phi(r_{ij}-d_{ij})\mathbf{n}_{ij} + k_1\phi(r_{ij}-d_{ij})\Delta v^t_{ij}\mathbf{t}_{ij} \qquad (13)$$

where the function $\phi(x)$ is equal to x if $x \geq 0$ and 0 otherwise. The vector $\mathbf{t}_{ij}$ is the tangential direction and Δv^t_{ij} is the tangential velocity difference. The r_{ij} term is the sum of the radii r_i and r_j, d_{ij} is the distance between the centers of mass of pedestrians i and j and k,k_1 are some large constants.

In our approach, we plan to model the choice of a leader by a pedestrian n with a random utility model where the alternatives are individuals in a given vicinity of n. The utility of each alternative is a function of the similarity of the walker's current movement with the movement of n. The leader plays a prominent role in the behavior models described above, compared to other individuals.

4.5 Calibration

The models as proposed will have many parameters describing a pedestrian's behavior. For the simulation to be realistic, valid values of these parameters are essential. Our idea is to link the simulator with a tracking program that will be used on real scenes to provide us with data on how pedestrians behave in actual situations.

The random utility models will be calibrated with trajectory data collected from real scenes, either using automatic tracking algorithms, or manually collected. Advanced models, like the Cross-Nested Logit model and the Network GEV models can be estimated by the package Biogeme (Bierlaire, 2003).

Ultimately, tracking algorithms will be coupled with the pedestrian simulator. As shown in figure 1, the benefit of this link between simulation and tracking is twofold:

- The quality of the simulation will be better because the parameters of the simulation model will be based on measurements done on real situations.
- As tracking is not infallible, for instance when a pedestrian is hidden by an obstacle or by another pedestrian, the simulation model can assign probabilities to various hypotheses made by the tracker and help it in choosing the correct one. Note that this is particularly appropriate for short term predictions.

Fully calibrating the simulation model is going to require large sets of video data from different situations such as halls, corridors, train stations, etc.

The goal of our research project is to integrate a pedestrian simulator with a tracking module to allow to forecast the scene evolution in time. What we aim to do is to calibrate our models with real data extracted from image sequences (crowd segmentation, human tracking). Due to its own nature, this kind of information is for the most part local and related to the individuals. In order to build realistic models and to calibrate them with real data, our attention will be focused mainly on the medium and short range models. What we expect to obtain from the tracking module is a trajectory for pedestrians, their directions and speed as well as some measures of density. What the simulator will have to provide will be the most likely chosen direction by pedestrians at the next step. As a consequence, all the long range behavioral patterns, as the destination choice, will not be of fundamental importance for the robustness and quality of our models.

5. Simulation

Several programs have been developed to simulate pedestrian behavior in various contexts, but the great majority of them seems to be aimed at building evacuation, especially in case of fire. We cite a few here:

- EXODUS (Gwynne *et al.*, 1997) is a software tool for simulating the evacuation of large numbers of people from buildings, airplanes, boats, etc.
- Simulex (Thompson and Marchant, 1994) is the evacuation simulation part of the IES Virtual Environment, a set of tools developed to aid in the design and evaluation of buildings.
- EVAS (Turner and Penn, 2002) is a simulator based on the *Visibility Graph Analysis* (see section 3.2).
- EVACSIM (Kopp, 1999) is an evacuation oriented simulator developed in Java. It is freely available, including source code.
- Finally, New Zealand Fire Service (2002) gives a list of more simulators of pedestrian behavior.

There are essentially two approaches to simulation: *time-based* and *event-based*. In the time-based approach, the simulation proceeds in fixed time steps and all actors of the simulation are updated at each of these steps. In the event-based approach, events (e.g. collisions) are generated and inserted into a priority queue and are then executed in increasing time order. For now, we have chosen a time-based approach because the model is simpler, but we might move to an event-based approach later if the evolution of our model requires each footstep to be controlled precisely.

We provide here a brief description of the design of our simulator. As the project is currently in its early stage, this design is likely to be modified in the future. However, most of the main issues are addressed.

Initialization A description of the space model described in Section 3.2 is the main input. Using an economics analogy, it can be seen as the “supply” side of the simulation. From the demand side, we use a time-dependent origin-destination matrix, where each cell correspond to an origin o, a destination d and a time interval Δt, exactly like the OD matrices used for transportation applications. The cells contain the number of individuals departing from o, targeting d during the time interval Δt.

From the time-dependent OD matrix, we create a population of pedestrians. Each pedestrian is associated with a list of characteristics (height, desired speed, age, etc.) The exact list of characteristics will obviously be determined by the behavioral models that will be used. This approach is consistent with the concept of demand simulation proposed by Antoniou *et al.* (1997) and Bierlaire *et al.* (2000). Also, we associate an itinerary with each pedestrian. An itinerary is defined as a sequence of intermediate targets, such that target k in the itinerary is visible from the position of target $k-1$, consistently with the network presentation presented in Figure 3.

Strategic decisions The strategic decisions of each pedestrian in the system are updated every Δs units of time. We design the size of Δs to be consistent with the time discretization Δt of the OD matrix, that is

$$\Delta t = k\Delta s$$

where $k \in \mathbb{N}$.

First, new pedestrians are loaded in the system, with an initial speed corresponding to their desired speed, and an initial direction corresponding to the next target in their itinerary. Then, the speed and direction of all individuals in the system are updated using the mid-range model described in Section 4.3 and a Monte-Carlo simulation.

Moving decisions The moving decisions of each pedestrian in the system are updated every Δm units of time. We design the size of Δm to be consistent with Δs, that is

$$\Delta s = \ell\Delta m$$

where $\ell \in \mathbb{N}$.

The position of all individuals in the system are updated using the short-range model described in Section 4.3 and a Monte-Carlo simulation.

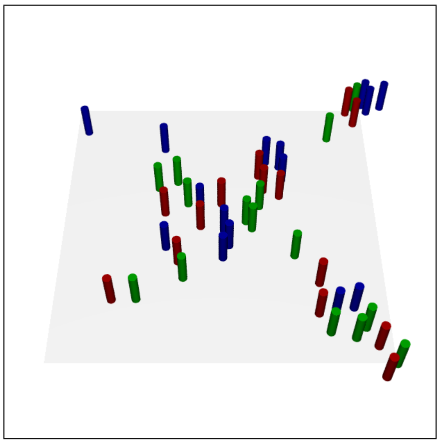

Figure 7: Example simulated situation

Figure 7 shows an example of a simple simulated situation generated by our prototype simulator. Pedestrians can move on a square domain 15 by 15 meters in size. Half the pedestrians are generated in the lower left corner and their goal is the upper right corner, the other half is generated in the upper left corner and their goal is the lower right corner. The desired trajectories cross in the middle of the square, where the two lines of pedestrians have to avoid each other.

6. Conclusions

Pedestrian simulation is becoming an important field of research, as the range of possible applications is widening. In this paper, we have tried to identify the behavioral aspects of pedestrian dynamics, and to describe how they are addressed in the literature. In addition, we have described our preliminary thoughts about the use of discrete choice models to capture this behavior, and their integration into a microscopic simulator of pedestrians designed to support image analysis and object tracking in the context of video surveillance.

There are several analogies with traffic simulation. However, two important issues are specific to pedestrian simulation. Firstly, the physical space cannot be represented by a network anymore, complicating the use of existing models. Secondly, and most importantly, the data collection is more complicated. Also, contrarily to traffic data, data about pedestrians movements are not institutionally recognized as useful, and consequently not collected on a regular basis.

We believe that addressing the "space model" challenge is feasible, as the sophistication of the models and the computer power is increasing (see Section 3.2). A lot of behavioral research is needed to obtain realistic results, and the validity of discrete choice models in this context must be assessed. But given their success in the context of traffic simulation, we are confident about this approach. The data challenge is much more complicated. We believe that the automatic analysis of video images is the way to go, although it does not cover all aspects of data collection, and focuses mainly on short-range behavior given the narrow range of a surveillance camera.

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