Discrete choice models of pedestrian behavior

Gianluca Antonini* Michel Bierlaire† Mats Weber†

September 16, 2004
ROSO Report 040916

Abstract

We propose a discrete choice framework for pedestrian dynamics, modeling short term behavior of individuals as a response to the presence of other pedestrians. We use a *dynamic and individual-based* spatial discretization, representing the physical space. We develop a model predicting where the next step of a walking pedestrian will be, at a given point in time. The use of the discrete choice framework is justified by its flexibility, the capacity to deal with individuals and the compatibility with agent-based simulation. The model is calibrated using data from actual pedestrian movements, manually taken from video sequences. We present two different formulations: a cross nested logit and a mixed nested logit. In order to verify the quality of the calibrated model, we have designed and developed a pedestrians simulator.

1 Introduction

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, 2004).

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). In this paper we use data produced by video recordings, similarly to Teknomo et al. (2000) and Teknomo et al. (2001).

*Signal Processing Institute, Swiss Federal Institute of Technology Lausanne, CH-1015 Lausanne, Switzerland, Gianluca.Antonini@epfl.ch

†Operations Research Group ROSO, Swiss Federal Institute of Technology Lausanne, Michel.Bierlaire@epfl.ch, Mats.Weber@epfl.ch

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 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 (Blue and Adler, 2001). 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).

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, the multi-level subjective utility maximization approach proposed by Hoogendoorn et al. (2002) and the model for pedestrian travel behavior in Hoogendoorn (2003) use a continuous space model. In all these approaches 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.

Important behavioral models in the context of pedestrian movements include a destination choice model, a route choice model, and a collision avoidance model.

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. Another important work, from a procedural point of view, is that of Hoogendoorn et al. (2002) and Daamen (2004). 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. 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.

The route choice problem is addressed by Borgers and Timmermans (1986a) as utility maximization problem. 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. Blue and Adler (2001) analyze 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.

Addressing 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 (2003) and Ramming (2001). As already mentioned above, 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 this paper, we assume that the destination and the route are known, generated by one of the many models listed above. We are interested in modeling the short range behavior of a pedestrian, as a response to her immediate environment and to the presence of other pedestrians.

2 The pedestrian movement model

At a given point in time, we model where the pedestrian will decide to be in a time horizon t. Typically, t is of the order of 1 second. The representation of the physical space plays an important role in the definition of the behavioral model. In our approach, we use a *dynamic and individual-based* spatial discretization representing the physical space. The basic elements that we use to define our spatial structure are illustrated in figure 1.

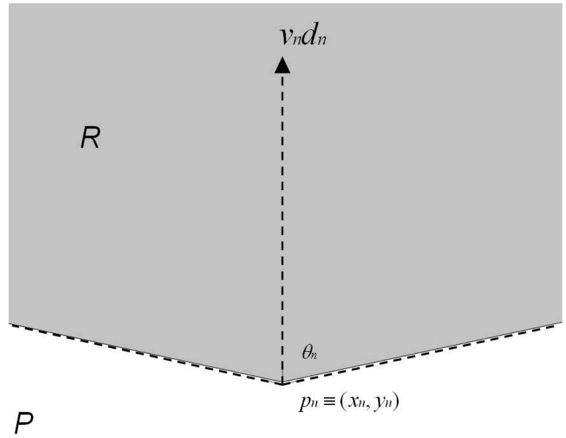


Figure 1: The basic geometrical elements of the space structure

The current position of the decision maker n is p_n, her current speed $v_n \in IR$, her current direction is $d_n \in IR^2$ (normalized, so that $\|d_n\| = 1$) and her visual angle is θ_n. The region of interest is situated in front of the pedestrian, within her visual field represented by the shaded area in Figure 1.

We have adopted a discrete choice methodology. The use of this approach is justified by the fact that discrete choice models are disaggregate, being therefore well compatible with the microscopic approach. Moreover, aggregate forecasting techniques allow the computation of macroscopic measurements from disaggregate models.
We need to appropriately define the universal choice set $\mathcal{C}$, the choice set $\mathcal{C}_n$ for a given individual n, the specification of the utility functions and the distribution of the random terms.

The choice set consists of a combination of speed regimes and directions. With regard to speed regimes, the decision-maker has three possibilities: keep the same speed v_n, slow down to $v_{dec} = (1-\gamma)v_n$ or accelerate up to $v_{acc} = (1+\gamma)v_n$, where v_n is the current speed of the decision maker and γ an acceleration/deceleration factor. In our model, we have selected $\gamma = 0.5$. With regard to direction, the visual angle $\theta_n = 170°$ is segmented into 11 radial cones, one cone capturing the decision not to change the direction (assumed to have an angle of 10°), and 10 cones capturing the decision to change direction, 5 at the left of the central cone, and 5 symmetrically defined at the right, as illustrated in Figure 2. Note that the apertures of those cones are not equal. Cones far from the central one have larger angles, as mentioned in Figure 2. Each cone is characterized in the model by its bisecting direction, denoted by d and assumed to be normalized, that is $\|d\| = 1$. The central cone is obviously characterized by the current direction d_n. Each alternative with speed v and direction d is characterized by the physical center of the corresponding cell in the space discretization, that is

$$c_{vd} = p_{\mathrm{n}} + vtd.$$

It is important to emphasize that this conceptual universal choice set, composed of $N = 33$ alternatives, is associated with different physical locations in space, depending on the current position and speed of the decision-maker. We refer to it as a *dynamic* and *individual-based* spatial discretization. This modeling idea enables to keep a choice set of reduced size, while allowing to account for the wide variability of possibilities depending on the location. A universal choice set derived from a simple static discretization of the space, similar to the model used by CA approaches, would have been too cumbersome and not sufficiently flexible in a discrete choice context.

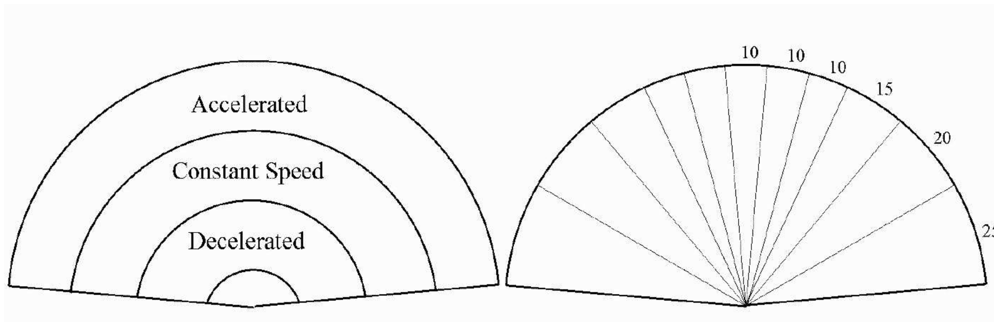


Figure 2: Choice set

For each individual, some cells can be declared unavailable because there is a physical obstacle blocking the corresponding space. Also, a maximum speed can be assigned to each individual (it can be fixed for the entire population, or drawn from a distribution). If the pedestrian is already walking at maximum speed, the cells corresponding to acceleration are not available.

We denote by c_{vdn} the alternative of individual n corresponding to speed regime $v \in \{v_{\text{n}}, v_{\text{dec}}, v_{\text{acc}}\}$, and direction d. The utility associated with this alternative is a random variable, for which the deterministic part is defined as

$$
\begin{array}{rcllc}
V_{vdn} & = & \beta_{\text{occ}} & \text{occupation}_{vd} & + \\
 & & \beta_{\text{dir}} & \text{direction}_{dn} & + \\
 & & \beta_{\text{dest}} & \text{destination}_{dn} & + \\
 & & \beta_{\text{angle}} & \text{angle}_{dn} & + \\
 & & \beta_{\text{acc}} & I_{\text{v,acc}}(v_n/v_{\text{max}})^{\lambda_{acc}} & + \\
 & & \beta_{\text{dec}} & I_{\text{v,dec}}(v_n/v_{\text{max}})^{\lambda_{dec}} &
\end{array}
\tag{1}
$$

where β_{occ}, β_{dir}, β_{dest}, β_{angle}, β_{acc}, λ_{acc}, β_{dec}, and λ_{dec} are unknown parameters to be estimated. The attributes describe the environment of the decision-maker. Namely, the position and direction of other pedestrians are important. We assume that there are N pedestrians potentially influencing the decision-maker. Each pedestrian k is at a position p_k, and walks toward a direction d_k. The attributes are defined as follows:

occupation$_{vd}$ It is defined as the weighted number of pedestrians being in the cone characterized by d, that is

$$\text{occupation}_{vd} = \sum_{k=1}^{N} I_{kd} e^{-\gamma_1 \|p_k - c_{vdn}\|} \tag{2}$$

where N is the total number of pedestrians in the environment, I_{kd} is one if pedestrian k belongs to the cone characterized by d and 0 otherwise,

$\|p_k - c_{vdn}\|$ is the distance between pedestrian k and the physical center of the alternative c_{vdn}. The role of γ_1 is to weight the importance of the distance in the formula. It is designed to capture the influence of the proximity of other pedestrians in the movements decisions as illustrated in Figure 3. We fix the value of γ_1 equal to 1.

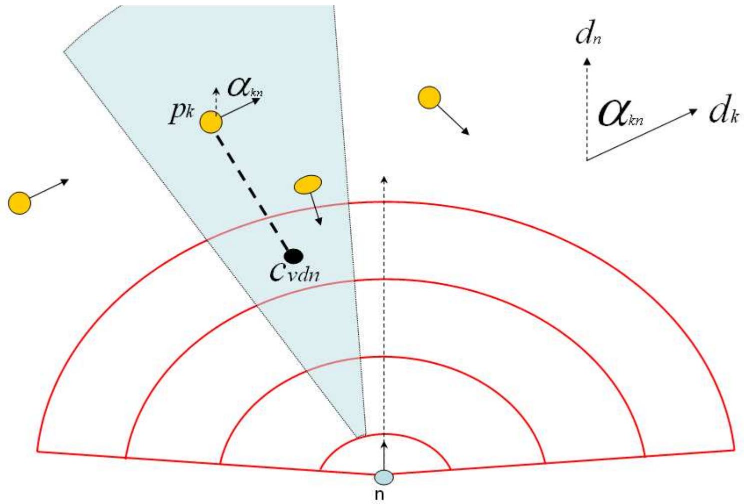


Figure 3: Occupation and angle

direction$_{dn}$ It is defined as the angle in degrees between direction d and direction d_n, corresponding to the central cone, as shown in Figure 4. It is designed to capture the propension of pedestrians to prefer their current direction, and not to erratically modify it.

destination$_{dn}$ If we denote by D_n the direction pointing toward the actual destination of decision-maker n, this attribute is defined as the angle in degrees between D_n and d, as shown in Figure 4. It is designed to capture the propension of pedestrians to move toward their destination.

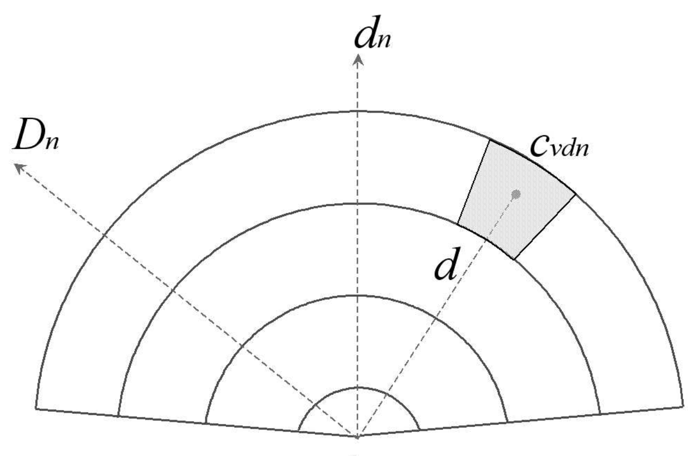


Figure 4: Destination and direction

angle$_{dn}$ It is defined as the weighted sum of angles between direction d_n and the walking directions of other pedestrians, that is

$$\text{angle}_d = \sum_{k=1}^{N} I_{kd} \alpha_{kn} e^{-\gamma_2 \|p_k - c_{vdn}\|} \tag{3}$$

where α_{kn} is the angle between d_n and d_k (Figure 3). The role of γ_2 is similar to the role of γ_1 in (2) (see Figure 3). This attribute is designed to capture the influence of the other pedestrians dynamics. Indeed, if a pedestrian k walks in the same direction (angle=0) or in the opposite direction (angle=π) with respect to the decision maker, we expect a different influence on the choice of the decision-maker. Note that, similarly to the definition of occupation$_{vd}$, close pedestrians play a more important influence than those who are further away. In our tests, we have fixed γ_2 to 1.

We finally comment on the last two terms of the utility function (1). The attribute $I_{\text{v,acc}}$ is 1 if $v = v_{\text{acc}}$, that is, if the alternative corresponds to an acceleration and 0 otherwise. $I_{\text{v,dec}}$ is similarly defined. If we write

$$\begin{aligned}
\tilde{\beta}_{\text{acc}} &= \beta_{\text{acc}} (v_n / v_{\text{max}})^{\lambda_{acc}}, \\
\tilde{\beta}_{\text{dec}} &= \beta_{\text{dec}} (v_n / v_{\text{max}})^{\lambda_{dec}},
\end{aligned}$$

the parameters $\tilde{\beta}_{\text{acc}}$ and $\tilde{\beta}_{\text{dec}}$ are simple dummies for the acceleration and deceleration alternatives, respectively, capturing the attractiveness of acceleration, respectively deceleration. We postulate that these dummies vary with the current speed of the decision-maker v_n. Indeed, someone who is already walking fast has less incentive to accelerate than someone who is walking slowly. The value of the parameter v_{max} is arbitrary. We have set it to the maximum speed observed in the data, for numerical convenience. β_{acc} is the value of the dummy associated with $v_n = v_{\text{max}}$ and λ_{acc} is the elasticity of the dummy with respect to speed, that is

$$\lambda_{acc} = \frac{\partial \tilde{\beta}_{\text{acc}}}{\partial v_n} \frac{v_n}{\tilde{\beta}_{\text{acc}}} \tag{4}$$

3 The random variable

In discrete choice models the utility of each alternative is a latent variable composed by a systematic part and a random part. Different assumptions about the random term give rise to different models. In this paper we present two different model formulations: a cross nested logit model and a mixed nested logit model.

3.1 Cross nested logit formulation

This model allows flexible correlation structures in the choice set keeping a closed form solution. The general formulation of the CNL model (see Bierlaire, 2001) is derived from the Generalized Extreme Value model (McFadden, 1978). The probability of choosing alternative i within the choice set C of a given choice maker is:

$$P(i|C) = \frac{\sum_m (\alpha_{im} y_i)^{\mu_m} \left(\sum_j (\alpha_{jm} y_j)^{\mu_m}\right)^{\frac{\mu}{\mu_m}-1}}{\sum_m \left(\sum_{j \in C} (\alpha_{jm} y_j)^{\mu_m}\right)^{\frac{\mu}{\mu_m}}} \tag{5}$$

where $\alpha_{jm} \geq 0 \; \forall j, m$; $\mu > 0$; $\mu_m > 0 \; \forall m$; $\mu \leq \mu_m \; \forall m$. We assume a correlation structure depending on the speed and direction and we identify five nests: *accelerated*, *constant*, *decelerated*, *central* and *not central*. This correlation structure is illustrated in figure 5. We fix the degrees of membership to the different nests (α_{jm}) to the constant value 0.5.

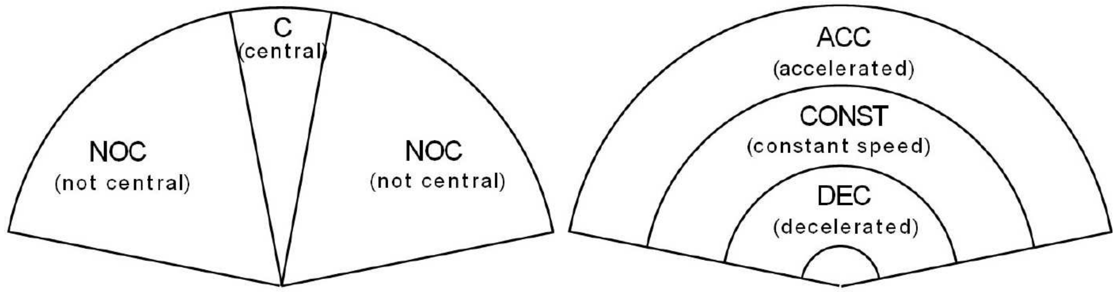


Figure 5: **left:** Nesting based on direction **right:** Nesting based on speed

3.2 Mixed nested logit formulation

The family of mixed models (logit kernel) is an hybrid between logit and probit and represents an effort to incorporate the advantages of each (Ben-Akiva and Bolduc, 1996,Walker, 2001). In our model we specify an error components formulation, where the correlation between alternatives still depends on speed and direction. The Gumbel terms capture the correlation in the speed related nests (accelerated, constant and decelerated), while 11 error components capture the correlation between alternatives along the 11 radial directions, one component for each direction. We show this structure in figure 6. The utility function as perceived by the individual n will have the following vector form:

$$U_n = V_n + \xi_k + \nu_s + \varepsilon_{nsk} \tag{6}$$

where $n = 1, ..., N$ is the index of alternatives, $k = 1, ..., 11$ the index of directions and $s \in S = \{\textit{accelerated}, \textit{constant}, \textit{decelerated}\}$ the index for the accelerated, constant and decelerated nests. The ξ_k are normally distributed with zero mean and variance σ_k, the ν_s are the Gumbel terms and ε_{nsk} represent the remaining unobserved components of the utility function. If the ξ_k are known, the model corresponds to a NL formulation:

$$\Lambda(i|\xi_k) = \frac{e^{\mu_{s(i)} V_i}}{\sum_{j \in s_{(i)}} e^{\mu_{s(i)} V_j}} \cdot \frac{e^{\mu \bar{V}_{s(i)}}}{\sum_{s \in S} e^{\mu \bar{V}_s}} \tag{7}$$

where

$$\bar{V}_s = \frac{1}{\mu_s} \ln \sum_{j \in s} \exp \mu_s V_j \tag{8}$$

and $\Lambda(i|\xi_k)$ is the probability that the choice is i conditional to ξ_k. The index $s_{(i)}$ refers to the nest s containing the alternative i. Since the ξ_k are unknown, the unconditional choice probability is given by:

$$P(i) = \int_{\xi} \Lambda(i|\xi) n(0, \Sigma) d\xi \tag{9}$$

where $n(0, \Sigma)$ is the joint density function of ξ (a product of k standard univariate normals) such that Σ is a 11×11 diagonal matrix.

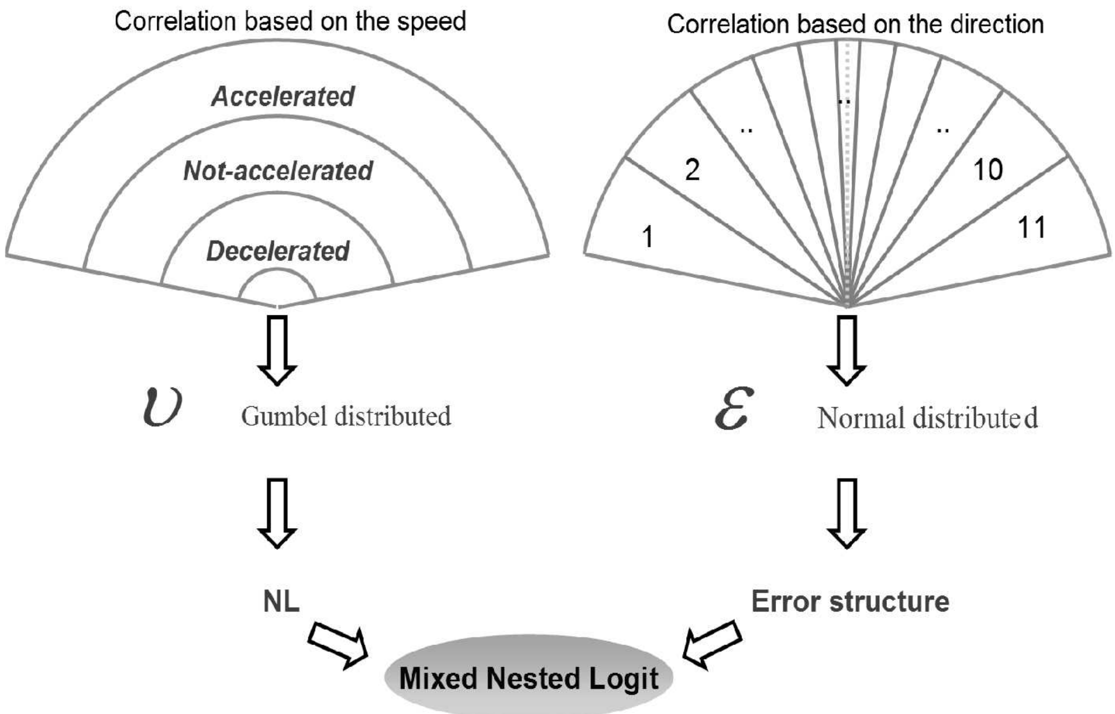


Figure 6: Correlation structure in the Mixed Nested Logit formulation

4 Data

The data set has been collected from digital video sequences of actual pedestrians. The scene used for data collection was filmed in the city of Lausanne, next to an entrance of a metro station. One frame from the video sequence is reported in Figure 7.

The fundamental condition for our data collection process is the calibration of the video camera used to make the video sequences in order to match the image with the walking plane. The theoretical formulation of the calibration problem consists in a system of non-linear equations where the variables are the camera parameters: height, focal distance and angles of the camera with respect to the horizon and the vertical axes. In order to simplify the problem, we have performed a direct measurement of the camera's height and we have fixed the angle with the

Figure 7: A frame from the test video sequence

vertical axes to 0°. The other two parameters have been computed using two reference points on the walking plane and using the correspondence between their *real-world* coordinates and *pixel-based* coordinates on the image plane, to obtain a unique correspondence between a point on the image plane and the same point on the walking plane.
The video sequences have been converted to AVI format with a frame rate equal to 10 frames/second. Globally, we have collected data for 36 pedestrians for a total of 1675 position observations, with a time interval of 3 frames (0.3 seconds). At each step, the observed choice made by the current decision maker has been measured 3 steps forward in time, i.e. 0.9 seconds. As a consequence, the last four positions of each trajectory are not used. Moreover, those observations corresponding to a static pedestrians ($v_n = 0$) and those corresponding to an observed choice out of the choice set, globally 107 observations, have been discarded. As a consequence, the actual number of observations used for the estimation is 1424.

At each step, we project the pixel-based coordinates of pedestrian k on the walking plane and we store the projected real-world coordinates. From the positions we derive the speed data:

$$\mathbf{v}_k^{t+1} = \frac{\mathbf{p}_k^{t+1} - \mathbf{p}_k^t}{\Delta t} \tag{10}$$

where $\mathbf{p}_k^t$ represent the position vector for pedestrian k at time t. The motion direction information is the vector:

$$\begin{pmatrix} arccos(v_{kx}^t / \|\mathbf{v}_k^t\|) \\ arccos(v_{ky}^t / \|\mathbf{v}_k^t\|) \end{pmatrix}$$

normalized; v_{kx}^t and v_{ky}^t are the observed speed vector components at time t. Table 1 shows some data statistics. For each pedestrian we report the trajectory length and the average values of the speed module, the angle between two consecutive directions and the angle between the current direction and the destination (taken as the last point in the pedestrian's trajectory). The speed values are expressed in m/s and all the angles are in degrees.

The average of the speed module over all the pedestrians is equal to 1.587 m/s, in line with other studies conducted in Singapore, USA and Britain (see

Tanaboriboon et al., 1986). The maximum observed value for the speed module is equal to $v_{max} = 7$ m/s. This unrealistic value is due to errors introduced by the approximated calibration of the camera, the manual collection process and the limited image resolution (for far pedestrians, few pixels on the image correspond to some meters on the real walking plane). The average, over all the pedestrians, of the angle between two consecutive directions is equal to 12.31°.

Finally, as an example, we report in Figure 4 the whole trajectories relative to two pedestrians (those labeled as 1 and 7, Figures 8(a),8(b)). We report also the related current directions (Figures 8(c),8(d)) and the angles between the current direction and the destination (Figures 8(e),8(f)).

5 Estimation results

All the models have been estimated using the Biogeme package (Bierlaire, 2003). We report in table 2 the results for the CNL formulation and in table 3 those for the mixed NL formulation. For both models, the signs of the estimated coefficients are consistent with our expectations. Indeed, the negative signs of the direction and destination coefficients reflect the tendency of an individual to keep her current direction and to move, if it is possible, toward the actual destination. The negative sign of the occupation coefficient reflects the fact that pedestrians will tend to prefer nearby spatial zones less crowded by other pedestrians. The speed related coefficients show that acceleration and deceleration are two distinct behavioral patterns. The negative sign of their coefficients reflect the intuitive fact that an individual will tend to keep her current speed value. The angle coefficient is not significant in the data set. Finally, the two elasticities parameters show that the tendency to accelerate reduces with higher speed values and the tendency to decelerate reduces with lower speed values. The interpretation of the parameters β_{acc} and λ_{acc} is illustrated in Figure 8.

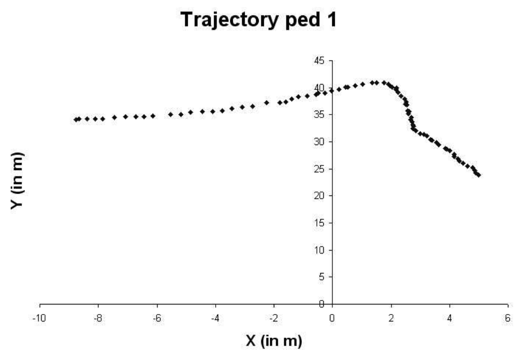
In the CNL model, only μ_{const}, capturing the correlation among alternatives with constant speed, and $\mu_{\text{not\_central}}$, capturing the correlation among alternatives not in the central cone, were significantly different from 1. In the Mixed Nested Logit model, not all σ parameters appear to be significantly different from 0. Moreover, the nest parameter for accelerating alternatives was not significantly different from 1. Although the μ_{dec} could have been rejected due to a 1.5329 t-test, we have preferred to keep it in the model.

The two models exhibit a similar efficiency, although the Mixed NL model is associated with a better likelihood. The ρ^2 is about 0.48 for both of them, which is a pretty satisfactory goodness-of-fit.

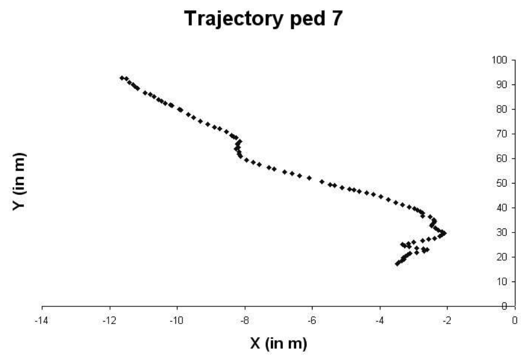
Pedestrian	**Length**	**Av. speed module**	**Av. direction changes**	**Av. dest/dir angle**
1	80	1.3121	17.2134	49.7448
2	76	1.3973	24.4686	50.7964
3	58	1.0791	12.7428	34.8595
4	67	1.1017	25.7278	41.4868
5	30	1.5074	12.3864	18.2588
6	31	1.4097	12.3808	23.8275
7	98	2.6599	4.76504	8.20303
8	78	1.4754	10.6729	8.47179
9	76	1.5056	7.66405	7.76997
10	74	1.5124	6.55338	6.54456
11	65	1.1749	15.7968	15.0215
12	64	1.2116	11.6047	14.6915
13	64	1.1829	10.6402	17.7533
14	64	1.2156	22.9867	25.7398
15	41	1.3720	19.3176	14.2739
16	44	1.4458	10.6938	10.3034
17	93	1.8020	6.11557	10.1469
18	26	1.3625	11.3140	9.86719
19	27	1.3936	7.43540	8.30740
20	31	1.4812	8.02392	7.06980
21	27	2.0810	5.45850	11.6286
22	26	2.2353	5.20697	5.66592
23	23	1.5080	15.0251	15.0056
24	21	1.6733	21.9325	21.7590
25	10	3.1347	8.78586	8.27878
26	8	3.1359	14.9502	11.7297
27	52	1.3508	16.9178	15.2413
28	48	1.4116	10.0380	9.23156
29	51	1.3118	10.7480	9.49111
30	50	1.3264	9.98961	12.2776
31	27	1.9956	6.48260	5.72725
32	33	2.0948	11.0510	9.17329
33	37	1.6379	13.1802	14.7109
34	29	1.2140	11.3827	9.26407
35	23	1.1076	9.48709	8.90465
36	23	1.3266	14.1527	17.8886

global average speed module: 1.587 m/s
global average direction difference: 12.31 degrees

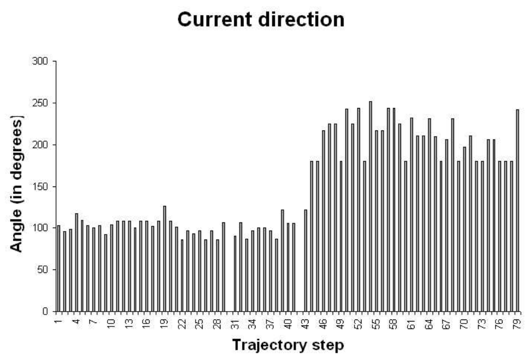
Table 1: Data statistics


Trajectory ped 1
Y (in m)
X (in m)
,

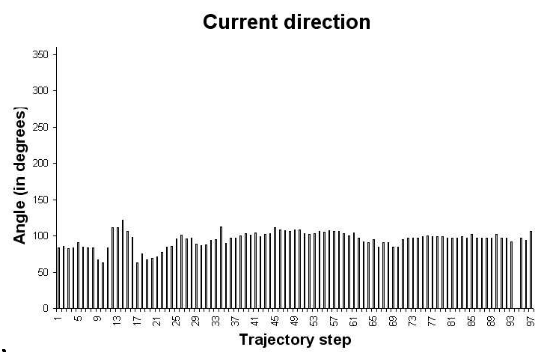
(a)


Trajectory ped 7
Y (in m)
X (in m)
,

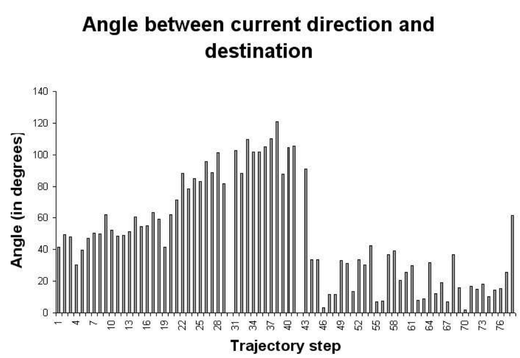
(b)


Current direction
Angle (in degrees)
Trajectory step
,

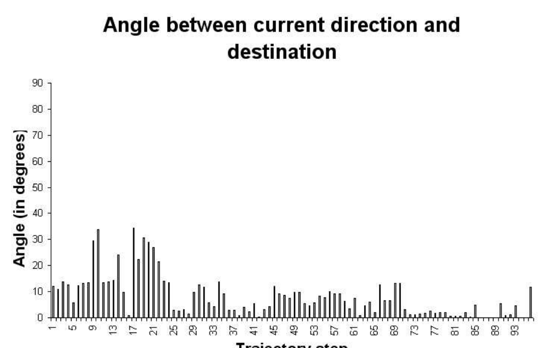
(c)


Current direction
Angle (in degrees)
Trajectory step
,

(d)


Angle between current direction and destination
Angle (in degrees)
Trajectory step
,

(e)


Angle between current direction and destination
Angle (in degrees)
Trajectory step
,

(f)

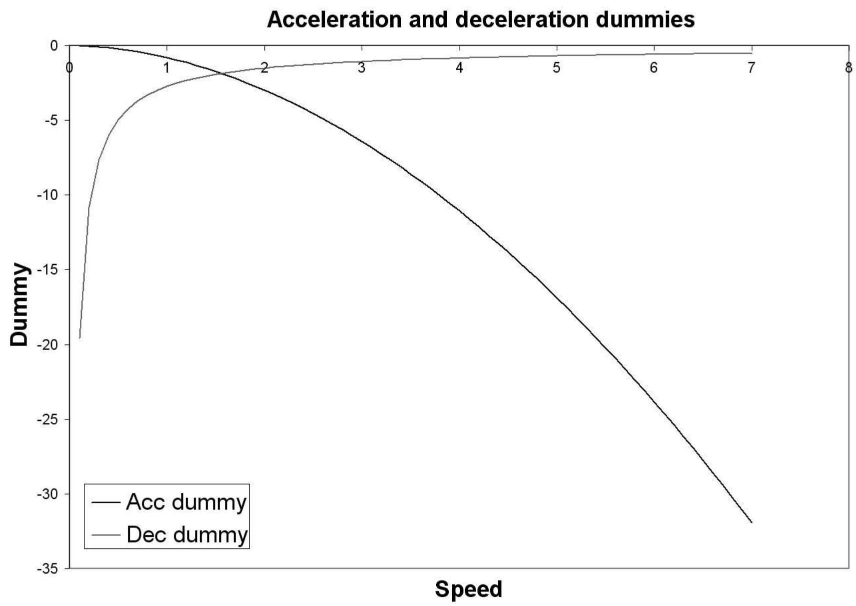


Figure 8: The parameters $\tilde{\beta}_{\mathrm{acc}}$ and $\tilde{\beta}_{\mathrm{dec}}$.

Variable name	**Coefficient estimate**	***t* test 0**	***t* test 1**
$\beta_{occupation}$	-1.7334	-3.0709	
$\beta_{direction}$	-0.0921	-11.5816	
$\beta_{destination}$	-0.0615	-11.8487	
β_{acc}	-33.6467	-4.3929	
β_{dec}	-0.5036	-6.2308	
λ_{acc}	1.8327	12.6680	
λ_{dec}	-0.8650	-8.9834	
μ_{const}	1.7956	5.7499	2.5477
$\mu_{not\_central}$	1.2867	8.8300	1.9676
Sample size =			1424
Number of estimated parameters =			9
Init log-likelihood =			-4979.03
Final log-likelihood =			-2579.25
Likelihood ratio test =			4799.55
Rho-square =			0.4819

Table 2: **CNL** estimation results

Variable name	**Coefficient estimate**	***t* test 0**	***t* test 1**
$\beta_{occupation}$	-1.5031	-2.7973	
$\beta_{direction}$	-0.1170	-10.5978	
$\beta_{destination}$	-0.0737	-9.3415	
β_{acc}	-32.7867	-4.4996	
β_{dec}	-0.4495	-5.4054	
λ_{acc}	1.7677	12.1902	
λ_{dec}	-0.8987	-8.7415	
σ_1	-1.4875	-2.3527	
σ_5	0.6850	3.7304	
σ_7	-0.9284	-5.3723	
σ_8	1.2338	5.9258	
σ_9	1.6298	5.7021	
σ_{10}	-2.3415	-4.8001	
μ_{noacc}	1.4067	10.5971	3.0636
μ_{dec}	1.3164	6.3777	1.5329
		Sample size =	1424
		Number of estimated parameters =	15
		Number of Halton draws =	2000
		Init log-likelihood =	-4979.03
		Final log-likelihood =	-2559.97
		Likelihood ratio test =	4838.11
		Rho-square =	0.4858

Table 3: **Mixed NL** estimation results

6 Simulation

In order to validate our model, we needed a way to "play" it so that we could verify if it represented realistic human behavior. We did indeed discover quite a few problems in earlier models by using the simulator — problems that we probably would not have seen without its help. For instance, initial versions of the model were instable with regard to speed: the pedestrians were either accelerating or decelerating to unreasonable speeds, which led us to introduce the speed elasticity parameters, which solved the problem by giving the pedestrians a stronger "will" to maintain a constant speed.

As shown in figure 9 the addition of the simulator to our system creates a feedback loop that results in an enhanced model.

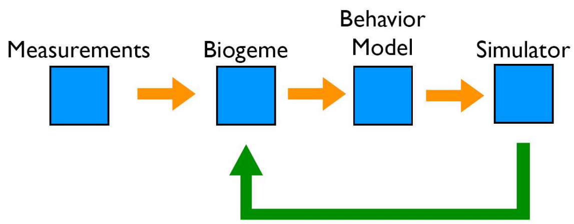


Figure 9: Model/simulator feedback

Other potential uses of simulation include capacity analysis, evacuation scenarios, incident scenarios, analysis of flow organization. Many developments exist in this area (see for instance Helbing et al., 2000, Kopp, 1999 and Gwynne et al., 1997) but to our knowledge, none of them uses a behavior model calibrated on actual data.

6.1 Design

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 currently use a time step of $\Delta t = 0.9s$ in our simulations, consistently with the model assumption.

The simulator was developed using object oriented design techniques and written in standard C++. As input, it accepts a description of the cross nested logit model given as follows:

- the β_i coefficients in (1),
- the μ and μ_m coefficients in (5),
- the α_{jm} coefficients in (5).

As output it produces images in a scene description language. We have successfully used *POVRay* for that purpose (`http://www.povray.org/`).

Following is a brief description of the algorithm inside our simulator:

- **Initialization**

  The input to our simulator is a time-dependent origin-destination matrix, where each cell corresponds 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 can be associated with a list of characteristics which can be adapted to specific model requirements. This approach is consistent with the concept of demand simulation proposed by Antoniou et al. (1997) and Bierlaire et al. (2000). Our CNL model does not contain socio-economic characteristics. 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 Bierlaire et al. (2003).

- **Moving decisions**

  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, at each time step (Δt), the utility value of each possible move is calculated for each pedestrian. These values are then transformed into probabilities consistent with the discrete choice model (see (5)) and each pedestrian's move is randomly selected according to these probabilities.

  Then, the speed and direction of all individuals in the system are updated to reflect the chosen move, using the model described previously in the paper.

  Then the position of all individuals in the system are updated using the formula $x_{i+1} = x_i + \Delta t \; v_i$, where x is the position, i the time step and v the speed.

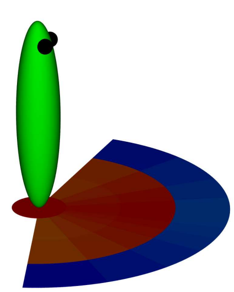


Figure 10: Pedestrian with choice set

Figure 10 shows a pedestrian as depicted by our simulator. Here the choice set is shown with a coloring based on the choice's probability, from blue = lowest probability to red = highest probability. In this example, the probability of accelerating is low (outer cells) and the choice with highest probability is the one straight ahead keeping the speed constant.

6.2 Results

The videos generated by the simulator can be found at

`http://ltswww.epfl.ch/ltsftp/antonini/`

Three different views can be generated by the simulator. In Figure 11 we illustrate the *normal view*. Pedestrians move on a real background (in front of the metro station in Lausanne) according to the calibrated CNL model. The *model view* is reported in Figure 12. The choice set is displayed using a color-based coding schema for the utilities (blue-red tones for low-high utility values, respectively). Finally, in Figure 13 we illustrate the *top view* obtained assuming to look at pedestrians from the top of the scene.

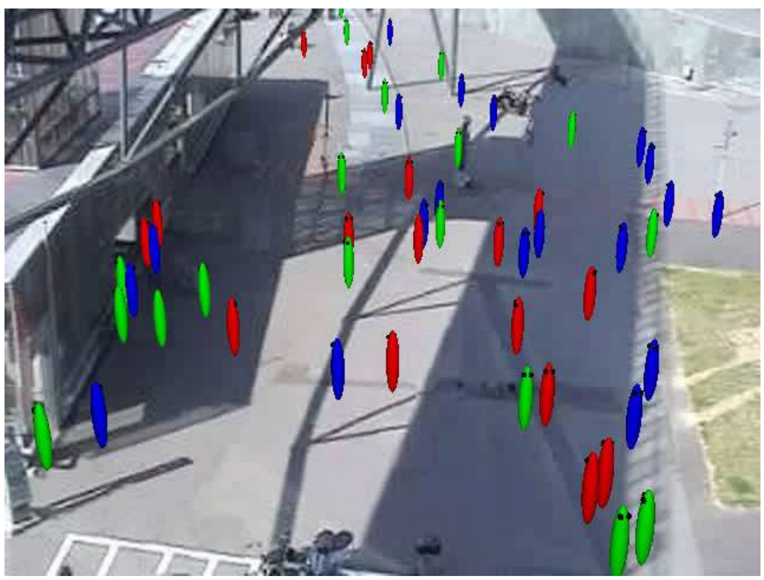


Figure 11: Normal view

7 Conclusion and future research

In this paper we have presented a discrete choice framework for pedestrian dynamics as an alternative to other existing models for pedestrian modeling. Our results show that the flexible and disaggregate nature of discrete choice models is well adapted to pedestrian behavior. The alternatives in the choice set show a strong spatial correlation. The cross nested logit and mixed nested logit formulations succeed in capturing these interdependencies in the choice set. The estimation results confirm our expectations. Explanatory variables related to the movement

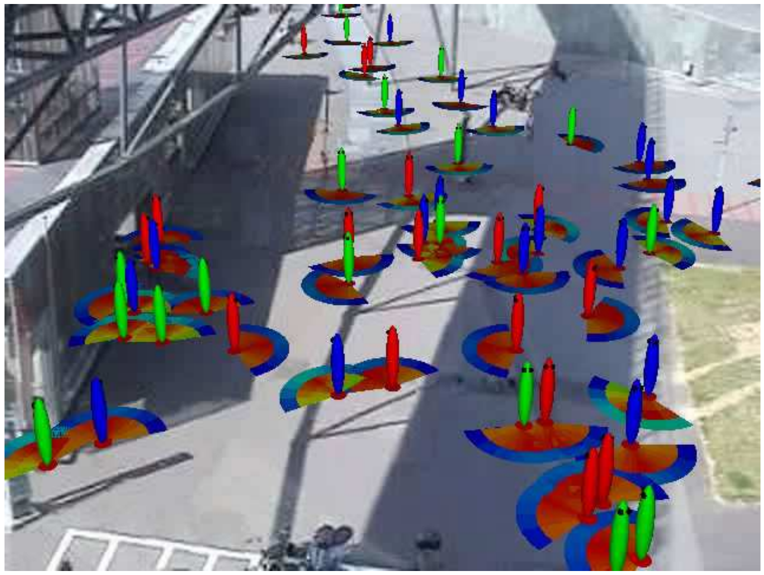


Figure 12: Model view

of pedestrian and to the presence of other individuals in the surrounding environment influence the short term behavior. The video sequences generated by the simulator show a rational behavior of the agents in the scene. They do not diverge in terms of speed and do not change erratically their direction.

With regard to applications, we have integrated the calibrated CNL formulation into a visual pedestrian tracking system, for automatic video surveillance. A promising new track of research is in fact the combination of tracking methods with mathematical models of the content of the image. In this spirit, the objective of this application is to combine tracking tools with a model simulating the content of the image, that is pedestrian movements. The obtained results show substantial improvements in detection and tracking of pedestrians in real complex scenarios, where standard image processing techniques can fail because of bad illumination conditions and image quality (see Venegas et al., 2004, Antonini et al., 2004 and S.Venegas et al., 2004).

We are currently working to extend the model to *high density* scenarios and to add an explicit model for obstacles. Another important issue is the calibration of the models using other larger data sets.

Acknowledgment

This work is supported by the Swiss National Science Foundation under the NCCR-IM2 project and by the Swiss CTI under project Nr. 6067.1 KTS, in collaboration with VisioWave SA, Ecublens, Switzerland.

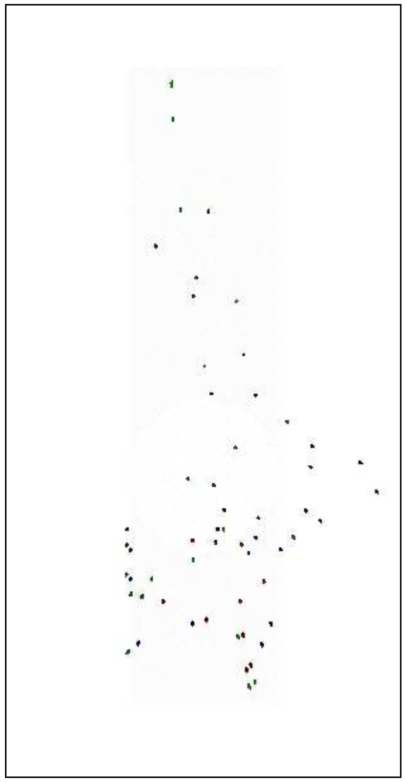


Figure 13: Top view

References

AlGadhi, S. A. H., Mahmassani, H. and Herman, R. (2002). A speed-concentration relation for bi-directional crowd movements, *in* M. Schreckenberg and S. Sharma (eds), *Pedestrian and Evacuation Dynamics*, Springer, pp. 3–20.

Antonini, G., Venegas, S., Thiran, J. and Bierlaire, M. (2004). Behavioral filtering of human trajectories for automatic-multi-track initiation, *Technical Report ITS-03-04*, Signal Processing Institute, EPFL.

Antoniou, C., Ben-Akiva, M., Bierlaire, M. and Mishalani, R. (1997). Demand simulation for dynamic traffic assignment, *Proceedings of the 8th IFAC Symposium on Transportation Systems*, Chania, Greece. http://its.mit.edu/pubs/pretrip.ps.

Ben-Akiva, M. and Bierlaire, M. (2003). Discrete choice models with applications to departure time and route choice, *in* R. Hall (ed.), *Handbook of Transportation Science, Second Edition*, Kluwer, pp. 7–37.

Ben-Akiva, M. and Bolduc, D. (1996). Multinomial probit with a logit kernel and a general parametric specification of the covariance structure. Paper presented at the 3rd Invitational Choice Symposium, Columbia University.

Ben-Akiva, M. E., Bergman, M. J., Daly, A. J. and Ramaswamy, R. (1984). Modeling inter-urban route choice behaviour, *in* J. Volmuller and R. Hamerslag (eds), *Proceedings from the ninth international symposium on transportation and traffic theory*, VNU Science Press, Utrecht, Netherlands, pp. 299–330.

Bierlaire, M. (2001). A general formulation of the cross-nested logit model, *Proceedings of the 1st Swiss Transportation Research Conference*, Ascona, Switzerland. www.strc.ch/bierlaire.pdf.

Bierlaire, M. (2003). BIOGEME: a free package for the estimation of discrete choice models, *Proceedings of the 3rd Swiss Transportation Research Conference*, Ascona, Switzerland.

Bierlaire, M., Antonini, G. and Weber, M. (2003). Behavioral dynamics for pedestrians, *in* K. Axhausen (ed.), *Moving through nets: the physical and social dimensions of travel*, Elsevier, pp. 1–18.

Bierlaire, M., Mishalani, R. and Ben-Akiva, M. (2000). General framework for dynamic demand simulation, *Technical Report RO-000223*, ROSO-DMA-EPFL Swiss Institute of Technology, CH-1015 Lausanne. http://rosowww.epfl.ch/mbi/demand-report.pdf.

Blue, V. J. and Adler, J. L. (2001). Cellular automata microsimulation for modeling bi-directional pedestrian walkways, *Transportation Research B* **35**(3): 293–312.

Borgers, A. and Timmermans, H. (1986a). City centre entry points, store location patterns and pedestrian route choice behaviour: A micro-level simulation model, *Socio-Economic Planning Sciences* **20**(1): 25–31.

Borgers, A. and Timmermans, H. (1986b). A model of pedestrian route choice and demand for retail facilities within inner-city shopping areas, *Geographical analysis* **18**(2): 115–128.

Bovy, P. H. L. and Stern, E. (1990). *Route choice: wayfinding in transport networks*, Vol. 9 of *Studies in Operational Regional Science*, Kluwer Academic Publishers, Dordrecht, NL.

Cascetta, E., Nuzzolo, A. and Biggiero, L. (1992). Analysis and modeling of commuters' departure time and route choice in urban networks, *Proceedings of the second international Capri seminar on urban traffic networks.*

Charlesworth, J. and Gunawan, E. (1987). The behavioural dynamics of route choice, *Traffic Engineering & Control* pp. 80–83.

Daamen, W. (2004). *Modelling passenger flows in public transport facilities*, PhD thesis, Delft University of Technology. The Netherlands TRAIL research school.

Dellaert, B. G., Arentze, T. A., Bierlaire, M., Borgers, A. W. and Timmermans, H. J. (1998). Investigating consumers' tendency to combine multiple shopping purposes and destinations, *Journal of Marketing Research* **35**(2): 177–188.

Gwynne, S., Galea, E. R., Lawrence, P., Owen, M. and Filippidis, L. (1997). Exodus. http://fseg.gre.ac.uk/exodus/.

Helbing, D., Farkas, I., Molnar, P. and Vicsek, T. (2002). Simulation of pedestrian crowds in normal and evacuation simulations, *in* M. Schreckenberg and S. Sharma (eds), *Pedestrian and Evacuation Dynamics*, Springer, pp. 21–58.

Helbing, D., Farkas, I. and Vicsek, T. (2000). Simulating dynamical features of escape panic, *Nature* **407**(28): 487–490.

Helbing, D. and Molnár, P. (1995). Social force model for pedestrian dynamics, *Physical review E* **51**(5): 4282–4286.

Hoogendoorn, S. (2003). Pedestrian travel behavior modeling, *10th International Conference on Travel Behavior Research*, Lucerne.

Hoogendoorn, S., Bovy, P. and W.Daamen (2002). Microscopic pedestrian wayfinding and dynamics modelling, *in* M. Schreckenberg and S. Sharma (eds), *Pedestrian and Evacuation Dynamics*, Springer, pp. 123–155.

Jiang, B. (1999). SimPed: simulating pedestrian flows in a virtual urban envoronment, *Journal of geographic information and decision analysis* **3**(1): 21–30.

Kessel, A., Klüpfel, H., Wahle, J. and Schreckenberg, M. (2002). Microscopic simulation of pedestrian crowd motion, *in* M. Schreckenberg and S. Sharma (eds), *Pedestrian and Evacuation Dynamics*, Springer, pp. 193–200.

Klüpfel, H., Meyer-König, M., Wahle, J. and Schreckenberg, M. (2000). Microscopic simulation of evacuation processes on passenger ships, *in* S. Bandini and T. Worsch (eds), *Theoretical and Practical Issues on Cellular Automata*, London, pp. 63–71.

Kopp, N. (1999). EvacSim, an evacuation simulation model. www.nathan.kopp.com/EvacSim/evacsim.html.

McFadden, D. (1978). Modelling the choice of residential location, *in* A. Karlquist *et al.* (ed.), *Spatial interaction theory and residential location*, North-Holland, Amsterdam, pp. 75–96.

Muramatsu, M., Irie, T. and Nagatani, T. (1999). Jamming transition in pedestrian counter flow, *Physica A* **267**: 487–498.

Nagel, K. (2004). Multi-agent transportation simulations. www.sim.inf.ethz.ch/papers/book/book.pdf.

Okazaki, S. (1979). A study of pedestrian movement in architectural space. Part 1: pedestrian movement by the application of magnetic models, *Trans. of A.I.J.* **283**: 111–119.

Parker, D. C., Manson, S. M., Janssen, M. A., Hoffmann, M. J. and Deadman, P. (forthcoming). Multi-agent systems for the simulation of land-use and land-cover change: a review, *Annals of the Association of American Geographers* . www.csiss.org/events/other/agent-based/papers/maslucc_overview.pdf.

Penn, A. and Turner, A. (2002). Space syntax based agent simulation, *in* M. Schreckenberg and S. Sharma (eds), *Pedestrian and Evacuation Dynamics*, Springer, pp. 99–114.

Quarantelli, E. L. (2001). Sociology of panic, *International Encyclopedia of the Social & Behavioral Sciences*, Elsevier Science.

Ramming, M. S. (2001). *Network Knowledge and Route Choice*, PhD thesis, Massachusetts Institute of Technology.

Schadschneider, A. (2002). Cellular automaton approach to pedestrian dynamics — Theory, *in* M. Schreckenberg and S. Sharma (eds), *Pedestrian and Evacuation Dynamics*, Springer, pp. 75–86.

Schultz, D. (ed.) (1964). *Panic behavior: discussion and readings*, Random House, New-York.

S.Venegas, G.Antonini, J.P.Thiran and M.Bierlaire (2004). Bayesian integration of a discrete choice pedestrian behavioral model and image correlation techniques for automatic multi object tracking, *Technical Report ITS 07.04*, Signal Processing Institute, EPFL.

Tanaboriboon, Y., Hwa, S. and Chor, C. (1986). Pedestrian characteristics study in singapore, *Journal of Transportation Engineering* **112**: 229–235.

Teknomo, K., Takeyama, Y. and Inamura, H. (2000). Data collection method for pedestrian movement variables, *Dimensi Teknik Sipil - Journal of Civil Engineering Science and Technology* **2**(1): 43–48.

Teknomo, K., Takeyama, Y. and Inamura, H. (2001). Tracking system to automate data collection of microscopic pedestrian traffic flow, *Proceedings of The 4th Eastern Asia Society For Transportation Studies*, pp. 11–25.

Thalmann, D. and Bandi, S. (1998). Space discretization for efficient human navigation, *Eurographics '98*, Computer Graphics Forum, pp. 195–206.

Venegas, S., Knebel, S. and Thiran, J. (2004). Multi-object tracking using particle filter algorithm on the top-view plan, *EUSIPCO*.

Walker, J. L. (2001). *Extended discrete choice models: integrated framework, flexible error structures, and latent variables*, PhD thesis, Massachusetts Institute of Technology.

Whynes, D., Reedand, G. and Newbold, P. (1996). General practitioners' choice of referral destination: A probit analysis, *Managerial and Decision Economics* **17**(6): 587.