Specification, estimation and validation of a pedestrian walking behaviour model

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Conference paper STRC 2008

STRC | **8th Swiss Transport Research Conference**
Monte Verità / Ascona, October 15-17, 2008

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Abstract

We propose and validate a model for pedestrian walking behaviour, based on discrete choice modelling. We are interested in modelling the short range behaviour in *normal* conditions, as a reaction to the surrounding environment and to the presence of other individuals. The term "normal" refers to non-evacuation and non-panic situations. Two main behaviours are identified: *unconstrained* and *constrained*. The unconstrained decisions are independent from the presence of others pedestrians whereas constrained decisions are induced by interactions with other individuals. Concerning the discrete choice model architecture, the spatial correlation between the alternatives is taken into account defining a cross nested logit model. The nests concern the direction cones and speed regimes. The model has been estimated by maximum likelihood on a Japanese dataset, using the free distributed Biogeme package. The dataset consists of pedestrians trajectories manually tracked from video sequences. It has been collected on a large pedestrian crossing road in Sendaï, Japan, on August 2000. The estimated coefficients are significant and their signs are consistent with our behavioural assumptions. The model has been validated using a two steps procedure. The first step consists in the specification validation using the estimation dataset, the second is the prediction evaluation using a Dutch dataset not involved in the estimation process. It is the experimental version of the Japanese dataset, collected at the Delft university in 2000-2001. The model has been compared to a simple model with more parameters (the utility of each alternative contains only a constant) to illustrate the importance of the explanatory variables. The proposed validation procedure underlines a good stability of the model and a good generalization performance.

Keywords

walking, pedestrian, operational level, microscopic model, discrete choice model, forecast model, cross nested logit model, estimation, validation, cross-validation

1 Introduction

Pedestrian behavior modeling is an important topic in different contexts. Architects are interested in understanding how individuals move into buildings to create optimal space designs. Transport engineers face the problem of integration of transportation facilities, with particular emphasis on safety issues for pedestrians. Recent tragic events have increased the interest for automatic video surveillance systems, able to monitor pedestrian flows in public spaces, throwing alarms when abnormal behavior occurs. Special emphasis has been given to more specific evacuation scenarios, for obvious reasons. In this spirit, it is important to define mathematical models based on behavioral assumptions, tested by means of proper statistical methods. Data collection for pedestrian dynamics is particularly difficult and only few models presented in the literature have been calibrated and validated on real data sets.

Previous methods for pedestrian behavior modeling can be classified into two main categories: *microscopic* and *macroscopic* models. In the last years much more attention has focused on microscopic modeling, where each pedestrian is modeled as an agent. Examples of microscopic models are the *social forces* model in Helbing and Molnar (1995) and Helbing et al. (2002) where the authors use Newtonian mechanics with a continuous space representation to model long-range interactions, and the multi-layer utility maximization model by Hoogendoorn et al. (2002) and Daamen (2004).

Leader-follower and collision avoidance behavior play a major role in explaining pedestrian movements. In order to include these aspects in our model, we took inspiration from previous car following models in transport engineering (including Newell, 1961, Herman and Rothery, 1965, Lee, 1966, Ahmed, 1999). The main idea in these models is that two vehicles are involved in a car following situation when a subject vehicle follows a leader, normally represented by the vehicle in front, reacting to its actions. In general, a sensitivity-stimulus framework is adopted. According to this framework a driver reacts to stimuli from the environment, where the stimulus is usually the leader's relative speed. Different models differ in the specification of the sensitivity term. This modeling idea is extended here and adapted to the more complex case of pedestrian behavior. We want to stress the fact that in driver behavior modeling a distinction between acceleration and direction (or lane) is almost natural (see Toledo, 2003 and Toledo et al., 2003), being suggested by the transport facility itself, organized into lanes. The pedestrian case is more complex, since movements are two-dimensional on the walking plane, where acceleration and direction changes are not easily separable. Constrained behavior in general, and collision avoidance in particular are also inspired by studies in human sciences and psychology, leading to the concept of *personal space* (see Horowitz et al., 1964, Dosey and Meisels, 1969 and Sommer, 1969).

The validation of pedestrian walking models is a difficult task, and has not been extensively reported in the literature. Berrou et al. (2007) and Kretz et al. (2008) validate their model by comparing real and simulated flows and densities at bottlenecks. Brogan and Johnson (2003) compare real walking paths with simulated paths using three different metrics: the distance error, that is the mean distance between the real and the simulated path for all simulation time steps, the area error, that is the area between the two paths, and the speed error, that is the mean difference in speed between the two paths for all simulation time steps.

2 Modeling framework

In this work we refer to the general framework for pedestrian behavior described by Daamen (2004). Individuals make different decisions, following a hierarchical scheme: *strategical*, *tactical* and *operational*. Destinations and activities are chosen at a strategical level; the order of the activity execution, the activity area choice and route choice are performed at the tactical level, while instantaneous decisions such as walking and stops are taken at the operational level. In this paper, we focus on pedestrian walking behavior, naturally identified by the operational level of the hierarchy just described. We consider that strategic and tactical decisions have been exogenously made, and are interested in modeling the short range behavior in *normal* conditions, as a reaction to the surrounding environment and to the presence of other individuals. By"normal" we mean non-evacuation and non-panic situations.

The motivations and the soundness of discrete choice methods have been addressed in our introductory work (Bierlaire et al., 2003, Antonini, Bierlaire and Weber, 2006, Antonini and Bierlaire, 2007). The objective of this paper is twofold. First, we aim to provide an extended disaggregate, fully estimable behavioral model, calibrated on real pedestrian trajectories manually tracked from video sequences. Second, we want to test the coherence, interpretability and generalization power of the proposed specification through a detailed validation on external data. Compared with Antonini, Bierlaire and Weber (2006), we present three important contributions: (i) we estimate the model using significantly more data representing revealed walking behavior, (ii) the model specification explicitly captures leader-follower and collision-avoidance patterns and (iii) the model is successfully validated both using cross-validation on the estimation data set, and forecasting validation on another experimental data set, not involved in the estimation process.

We illustrate in Figure 1 the behavioral framework. Unconstrained decisions are independent of the presence of other pedestrians and are generated by subjective and/or unobserved factors. The first of these factors is represented by the individual's destination. It is assumed to be exogenous to the model. The second factor is represented by the tendency of people to keep their current direction, minimizing their angular displacement. Finally, unconstrained acceleration and deceleration are dictated by the individual's desired speed. The implementation of these ideas is made through the three unconstrained patterns indicated in Figure 1.

We assume that behavioral constraints are induced by interactions with other individuals nearby. The *collision avoidance* pattern is designed to capture the effects of

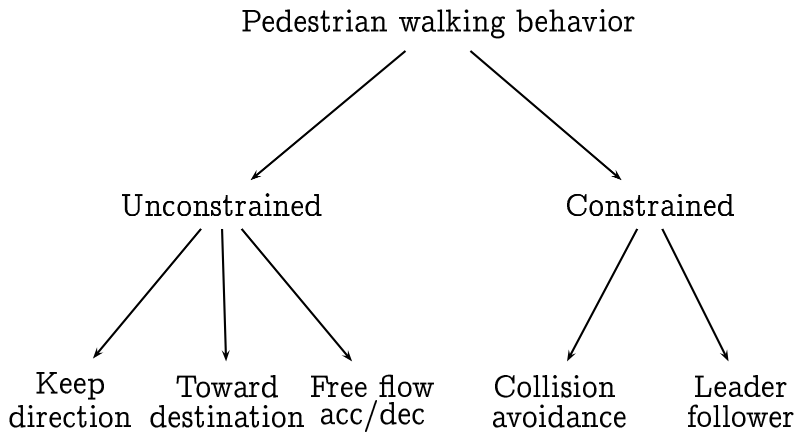


Figure 1: Conceptual framework for pedestrian walking behavior

possible collisions on the current trajectory of the decision maker. The *leader-follower* pattern is designed to capture the tendency of people to follow another individual in a crowd, in order to benefit from the space she creates.

The discrete choice model introduced by Antonini, Bierlaire and Weber (2006) is extended here. The basic elements are the same and summarized below. Pedestrian movements and interactions take place on the horizontal walking plane. The spatial resolution depends on the current speed vector of the individuals. The geometrical elements of the space model are illustrated in Figure 2.

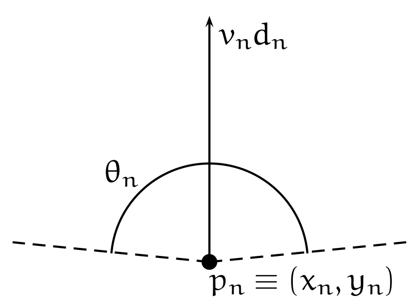
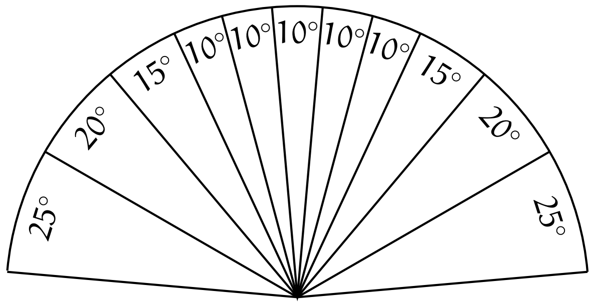
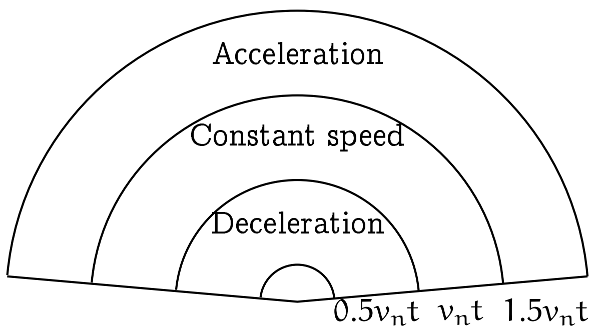


Figure 2: The basic geometrical elements of the space structure

In a given coordinate system, the current position of the decision maker n is $p_n \equiv (x_n, y_n)$, her current speed $v_n \in \mathbb{R}$, her current direction is $d_n \in \mathbb{R}^2$ (normalized such that $\|d_n\| = 1$) and her visual angle is θ_n (typically, $\theta_n = 170°$). The region of interest is situated in front of the pedestrian, ideally overlapping with her visual field. An individual-specific and adaptive discretization of the space is obtained to generate a set of possible places for the next step. Three speed regimes are considered. The individual can accelerate to 1.5 times her speed, decelerate to half time her speed, or maintain her current speed. Therefore, the next position will lie in one of the zones, as depicted in Figure 3(b). For a given time step t (typically, 1 second), the *deceleration* zones range from $0.25v_nt$ to $0.75v_nt$, with the center being at $0.5v_nt$, the *constant speed* zones range from $0.75v_nt$ to $1.25v_nt$, with the center being at v_nt, and the *acceleration* zones range from $1.25v_nt$ to $1.75v_nt$, with the center being at $1.5v_nt$. With respect to the direction, a discretization into 11 radial directions is used, as illustrated in Figure 3(a), where the angular amplitudes of the radial cones are reported in degrees.



(a) Discretization of directions



(b) Discretization of speed regimes

Figure 3: The spatial discretization.

A choice set of 33 alternatives is generated where each alternative corresponds to a combination of a speed regime v and a radial direction d, as illustrated in Figure 4. Each alternative is identified by the physical center of the corresponding cell in the spatial discretization c_{vd}, that is

$$c_{vd} = p_n + vtd, \tag{1}$$

where t is the time step. The choice set varies with direction and speed and so does the distance between an alternative's center and other pedestrians.

3 The model

Individuals walk on a 2D plane and we model two kinds of behavior: changes in direction and changes in speed, i.e. accelerations. Five behavioral patterns are defined:

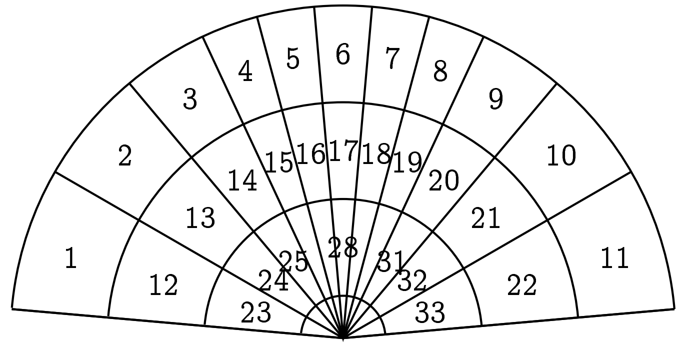


Figure 4: Choice set representation, with numbering of alternatives

keep direction, toward destination, free flow acceleration, leader-follower and collision-avoidance. In a discrete choice context, they have to be considered as terms entering the utility functions of each alternative. The utilities describe the space around the decision maker and under the assumption of rational behavior, the individual chooses the location (alternative) with the maximum utility. The details of the model are discussed in a referenced article (see Robin et al., n.d.).

4 Data

The data set used to estimate the model consists of pedestrian trajectories manually tracked from video sequences.

It was collected in Sendai, Japan, in August 2000 (see Teknomo et al., 2000, Teknomo, 2002). The video sequence was recorded from the 6th floor of the JTB parking building, situated at an important pedestrian crossing. Two main pedestrian flows cross the street, giving rise to a large number of interactions. A frame extracted from this video is represented in Figure 5.

The data set consists of 190 pedestrian trajectories, manually tracked at a rate of 2 processed frames per second, for a total number of 10200 position observations. The mapping between the image plane and the walking plane was performed by Arsenal Research (Bauer, 2007) using a 3D-calibration with the standard DLT algorithm (Shapiro, 1978). The reference system on the walking plane has the origin arbitrarily placed at the bottom left corner of the cross-walk. The x axis represents the width of the crossing while the y axis represents the length.

For each frame, the following information for each visible pedestrian was collected: (i) the time t corresponding to the frame f (in this case $t = f/2$), (ii) the pedestrian identifier n, and (iii) the coordinates $p_n^f = (x_n^f, y_n^f)$ identifying the location of the pedestrian in the walking plane. In Figure 6 we report the speed histogram and in Table 1 the speed statistics.

(a) Japanese scenario

Figure 5: A frame from the Japanese video

Mean	1.31
Standard Error	0.012
Median	1.27
Mode	1.28
Standard Deviation	0.37
Minimum	0.43
Maximum	4.84

Table 1: Speed statistics (m/sec). Note that *standard error* is the estimated standard deviation of the sample mean

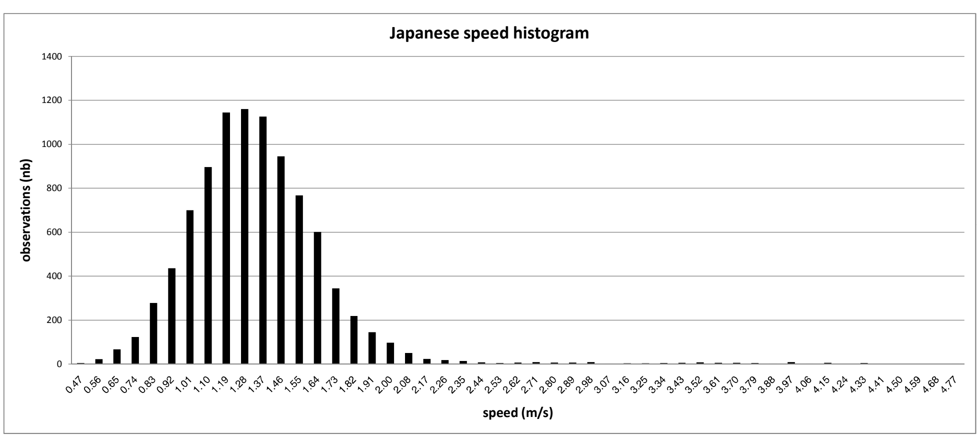


Figure 6: Speed histogram

Then, a specific choice set (see Figure 4) was constructed for each pedestrian, based on (1) where $t = 1$ sec (that is, 2 frames), $v = v_n$ for constant speed alternatives, $v = 0.5v_n$ for decelerated alternatives, $v = 1.5v_n$ for accelerated alternatives, $d = d_n$ for alternatives in cone 6 (alt. 6, 17, 28), and $d = \text{rot}(d_n, \zeta)$ is obtained by rotating d_n around p_n with an angle ζ corresponding to the cone, that is

$$\begin{array}{llll} \text{Cone 1:} & \zeta = 72.5°, & \text{Cone 11:} & \zeta = -72.5°, \\ \text{Cone 2:} & \zeta = 50°, & \text{Cone 10:} & \zeta = -50°, \\ \text{Cone 3:} & \zeta = 32.5°, & \text{Cone 9:} & \zeta = -32.5°, \\ \text{Cone 4:} & \zeta = 20°, & \text{Cone 8:} & \zeta = -20°, \\ \text{Cone 5:} & \zeta = 10°, & \text{Cone 7:} & \zeta = -10°. \end{array}$$

For each cell in the choice set, each variable interfering in the utility was then computed (see Robin et al., n.d.). Note that the destination of each individual was defined by her location in the last frame where she is visible. Finally, the chosen alternative has been identified as the cell containing the pedestrian's location after 1 second, that is p_n^{f+2}. In the rare instances where p_n^{f+2} did not belong to any cell (because of numerical errors due to poor image resolution, or extreme speed variations), the corresponding piece of data was removed from the sample (a total of 919 observations). We represent in Figure 7 selected generated choice sets on a given trajectory (representing them all would have been unreadable).

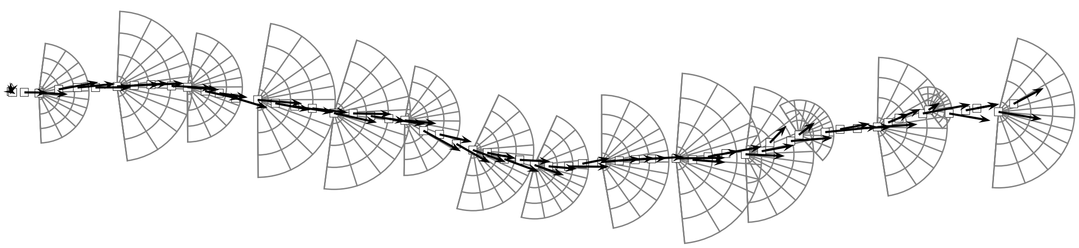


Figure 7: Example of one manually tracked trajectory with choice sets

We obtain a total of 9281 observations from 190 pedestrians. In Figure 8 we report the frequency of the revealed choices as observed in the data set. The three peaks in the distributions arise on the central alternatives (6, 17, 28), as expected. Note that cells 1, 12, 23 and 33 were never chosen in this sample. A summary of the observations across the nests is detailed in Table 2.

5 Estimation results

Table 3 presents the estimation results. The parameters were estimated using Biogeme (Bierlaire, 2003, biogeme.epfl.ch). All estimates have the expected sign.

In addition to the proposed model, we analyze also a simple model, where the utility of each alternative is represented only by an alternative specific constant. This constant-only model perfectly reproduces the observed shares in the sample, with 28 parameters

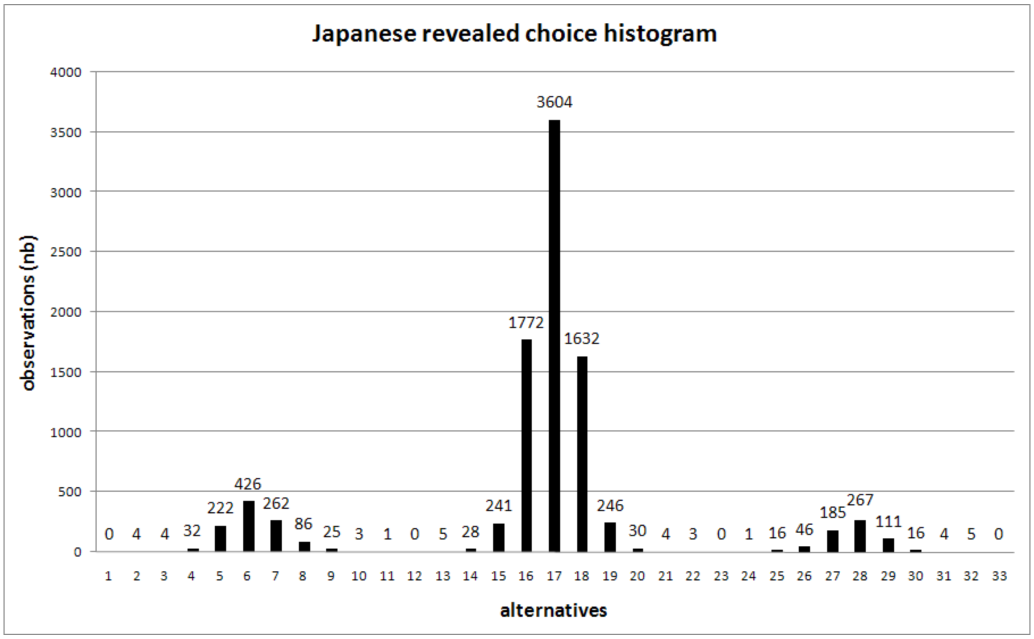


Figure 8: Revealed choices histograms

Nest	# steps	% of total
acceleration	1065	11.48%
constant speed	7565	81.51%
deceleration	651	7.01%
central	4297	46.30%
not central	4984	53.70%

Table 2: Number of chosen steps in each nest for the real data set

(33 alternatives, minus 4 which are never chosen, minus one constant normalized to 0), but does not capture any causal effect. With this model, the loglikelihood drops from -13944.74 to -17972.03, illustrating the statistical significance of the proposed specification. Note that a classical likelihood ratio test is not appropriate here, as the hypotheses are not nested. We believe that a more rigorous test is not really necessary given the huge jump in loglikelihood value.

Sample size = 9281	Init log-likelihood = -32451
Nbr of estimated parameters = 24	Final log-likelihood = -13944.74
$\bar{\rho}^2 = 0.570$	Likelihood ratio test = 37013

Table 3: **CNL** estimation results for the Japanese data set

6 Model validation

Two data sets are used for validation: the Japanese data set used for estimation and described in Section 4, and a data set collected in the Netherlands, which was not involved at all in the estimation of the parameters.

6.1 Japanese data set: validation of the model

We first apply our model with the parameters described in Table 3 on the Japanese data set, using Biosim (Bierlaire, 2003). For each observation n, we obtain a probability distribution $P_n(i)$ over the choice set.

Figure 9 represents the histogram of the probability value $P_n(i_n^*)$ assigned by the model to the chosen alternative i_n^* of each observation n, along with the hazard value $1/33$ (where 33 is the number of alternatives). We consider observations below this threshold as outliers. There are only 7.10% of them. As a comparison, there are 19.90% of outliers with the constant-only model.

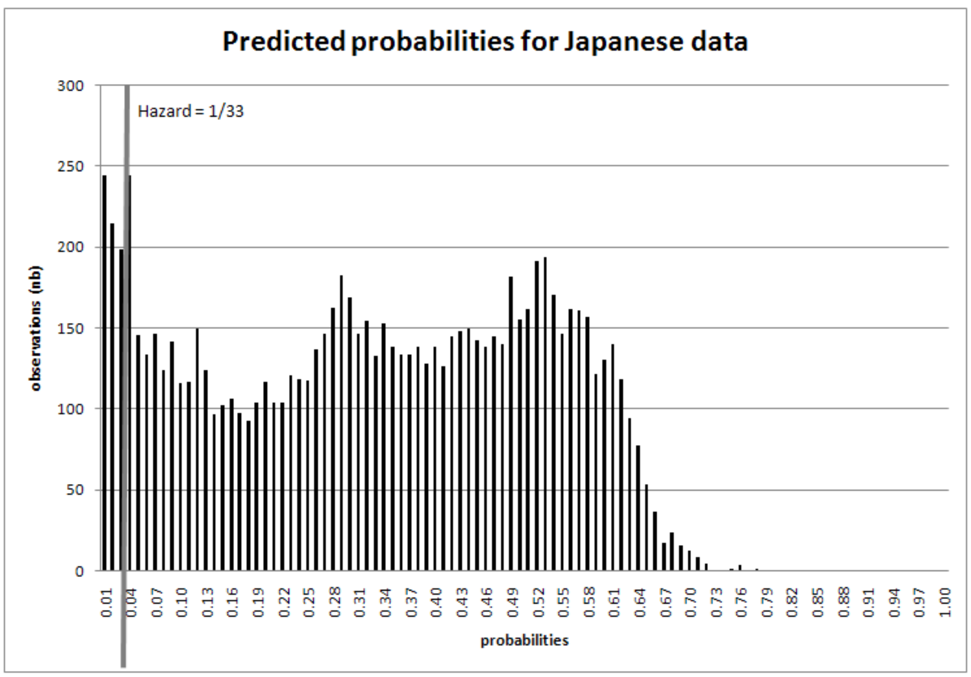


Figure 9: Predicted probabilities of the Japanese data

The top part of Figure 10 reports, for each i, $\sum_n P_n(i)$, and the bottom part reports $\sum_n y_{in}$, where y_{in} is 1 if alternative i is selected for observation n, 0 otherwise. As expected, the two histograms are similar, indicating no major specification error.

This is confirmed when alternatives are aggregated together, by directions (see Table 4) and by speed regimes (see Table 5). For a group Γ of alternatives, the quantities

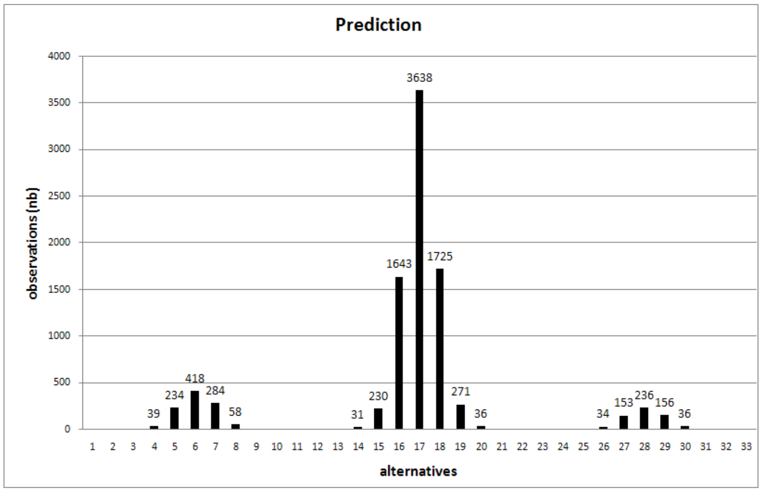
$$\begin{aligned} M_\Gamma &= \sum_n \sum_{i\in\Gamma} P_n(i), \\ R_\Gamma &= \sum_n \sum_{i\in\Gamma} y_{in}, \end{aligned}$$

and

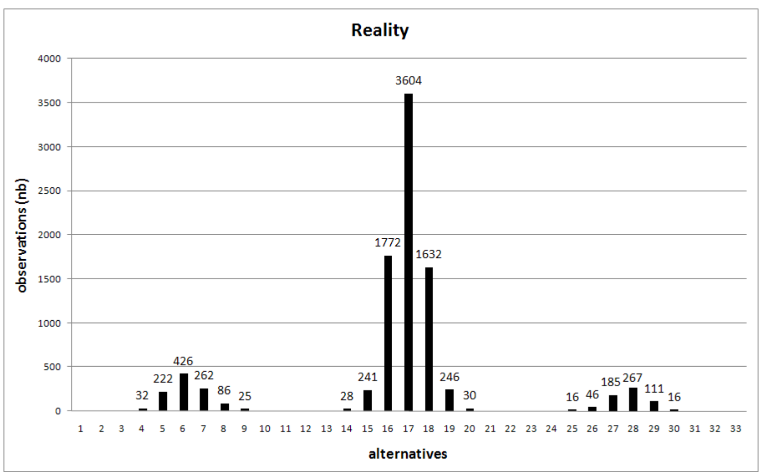
$$(M_\Gamma - R_\Gamma)/R_\Gamma$$

are reported in columns 3, 4 and 5, respectively, of these tables.

The relative errors showed in Table 4 and Table 5 are low, except for groups of alternatives with few observations, that is groups corresponding to extreme left and extreme right directions.



(a) Predicted shares



(b) Observed shares

Figure 10: Predicted and observed shares for the Japanese data set

6.2 Japanese data set: validation of the specification

In order to test the proposed specification, we have performed a cross validation done on the Japanese data set. It consists in splitting the data set into 5 subsets, each containing 20% of the observations. We perform 5 experiments. For each of them, one of the five subsets is saved for validation purposes, and the model is re-estimated

Cone	Γ	M_Γ	R_Γ	$(M_\Gamma - R_\Gamma)/R_\Gamma$
Front	$5-7, 16-18, 27-29$	8486.16	8481	0.0006
Left	$3, 4, 14, 15, 25, 26$	348.86	367	−0.0494
Right	$8, 9, 19, 20, 30, 31$	419.29.	407	0.0302
Extreme left	$1, 2, 12, 13, 23, 24$	12.29	10	0.2292
Extreme right	$10, 11, 21, 22, 32, 33$	14.39	16	−0.1004

Table 4: Predicted (M_Γ) and observed (R_Γ) shares for alternatives grouped by directions with the Japanese data set

Area	Γ	M_Γ	R_Γ	$(M_\Gamma - R_\Gamma)/R_\Gamma$
acceleration	$1-11$	1059.85	1065	−0.0048
constant speed	$12-22$	7588.28	7565	0.0031
deceleration	$23-33$	632.87	651	−0.0279

Table 5: Predicted and observed shares for alternatives grouped by speed regime with the Japanese data set.

on the remaining 4 subsets. The same procedure has been applied with the constant-only model. The proportion of outliers for each experiment is reported in Table 6. We observe that they are consistent with 7.10% (for our model) and 19.90% (for the constant-only model) of outliers obtained with the complete data set, illustrating the robustness of the specification.

Model	**Exp. 1**	**Exp. 2**	**Exp. 3**	**Exp. 4**	**Exp. 5**
Proposed spec.	8.62%	6.52%	7.44%	7.87%	5.87%
Constant only	20.79%	20.70%	17.13%	19.88%	18.64%

Table 6: Summary of the cross-validation performed on the Japanese data set

The above analysis indicates a good specification and performance of the model. However, it is not sufficient to fully validate it. Consequently, we perform now the same analysis on a validation data set, not involved in the estimation of the model.

6.3 Dutch data set: validation of the model

This data set was collected at Delft University, in the period 2000-2001 (Daamen and Hoogendoorn, 2003b, Daamen and Hoogendoorn, 2003a, Daamen, 2004) where volunteer pedestrians (about 80) were called to perform specific walking tasks in a controlled experimental setup (experiment 4 in Daamen and Hoogendoorn, 2003a)

For the purposes of our validation procedure we use the subset of the Dutch data set corresponding to a bi-directional flow. This situation is the experimental version of the Japanese data set, which corresponds to a walkway. The subset includes 724 subjects for 47481 observed positions, collected by means of pedestrian tracking techniques on video sequences, at a frequency of 10Hz, that is 10 frames per second. In Figure 11 we report one frame from the experimental scenario.

For each frame, we collected for each visible pedestrian the time t corresponding to the frame f (in this case $t = f/10$), the pedestrian identifier n, and the coordinates $p_n^f = (x_n^f, y_n^f)$ identifying the location of the pedestrian in the walking plane. From these raw data, we derived the current direction and speed of each pedestrian using the current and previous frames, that is

$$\begin{aligned} d_n &= p_n^f - p_n^{f-1}, \\ v_n &= \|d_n\|/0.1 = 10\|d_n\|. \end{aligned}$$

Consistent with the model assumptions, the chosen alternative has been identified as the cell containing the pedestrian's location after 1 second, that is p_n^{f+10}.

A summary of the observations across nests is detailed in Table 7. Note the very low number of decelerations and accelerations, probably due to the experimental nature of the data.

Figure 11: A representative frame from the video sequences used for data collection

Nest	# steps	% of total
acceleration	1273	2.68%
constant speed	45869	96.61%
deceleration	339	0.71%
central	20950	44.12%
not central	26531	55.88%

Table 7: Number of chosen steps in each nest for Dutch data

We compare the observed choices for the Japanese and the Dutch data set in Table 8 and Figure 12. Table 8 reports the percentage of observations for cells at the extreme left of the choice set (alts. 1, 2, 12, 13, 23, 24), the left part (alts. 3, 4, 14, 15, 25, 26), the front (alts. 5-7, 16-18, 27-29), the right (alts. 8, 9, 19, 20, 30, 31) and the extreme right (10, 11, 21, 22, 32, 33). Figure 12 reports normalized observation, that is, for each alternative i, $\sum_n y_{in}/N$, where y_{in} is 1 if alternative i is selected for observation n, 0 otherwise, and N is the total number of observations. We observe a great similarity in the observed proportions, except for alternatives corresponding to accelerations and decelerations. This suggests that a simple model, with only alternative specific constants, may actually perform well on this data set. We show below, however that this is not the case.

Data set	Extreme left	Left	Front	Right	Extreme right
Japanese	0.11%	3.95%	91.38%	4.39%	0.17%
Dutch	0.06%	4.40%	91.35%	4.15%	0.04%

Table 8: Comparison between Japanese and Dutch data sets for the observations proportions in the direction's cones

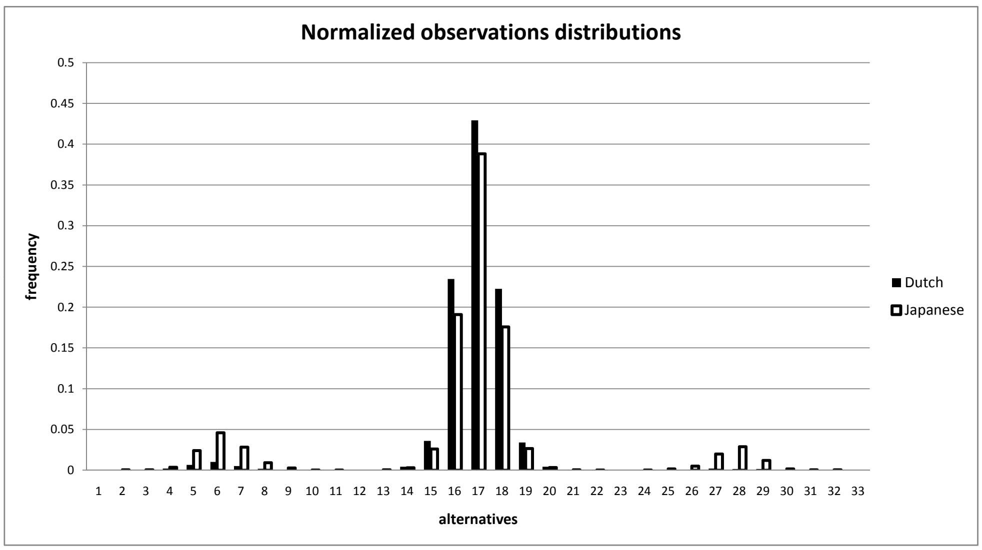


Figure 12: Comparison between the Japanese and Dutch normalized observation distributions across the alternatives

We applied our model with the parameters described in Table 3 on the Dutch data set, using the Biosim package. For each observation n, we obtain a probability distribution $P_n(i)$ over the choice set.

Figure 13 represents the histogram of the probabilities $P_n(i_n^*)$ of the chosen alternatives as predicted by the model, as well as the hazard value 1/33 (where 33 is the number of alternatives) illustrating the prediction of a purely random model with equal probabilities. Again, we consider observations below this threshold as outliers. We observe that there are 2.41% of them. This is good news, as it is actually less than for the data set used for parameter estimation. The shape of the curve, as well as the low number of outliers are signs of the good performance of the model. When we compare it with predictions obtained with the constant-only model (Figure 14), the superior forecasting potential of our model is clear.

The significant superiority of our model over the constant-only model is also illustrated by comparing the proportion of outliers (2.41% vs. 10.31%) or the loglikelihood (-51303.58 vs. -77269.28, as detailed in Table 14).

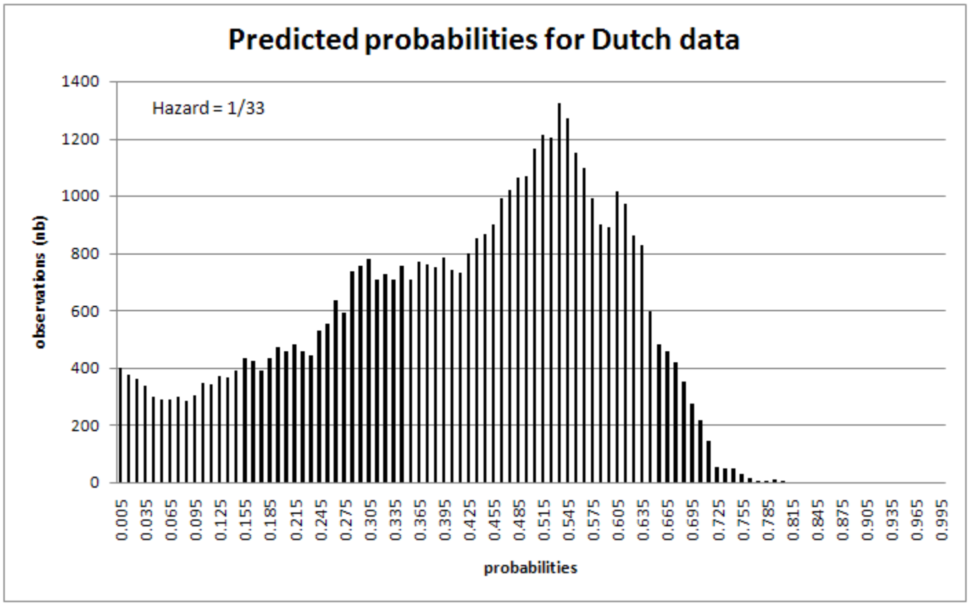


Figure 13: Prediction with the proposed model

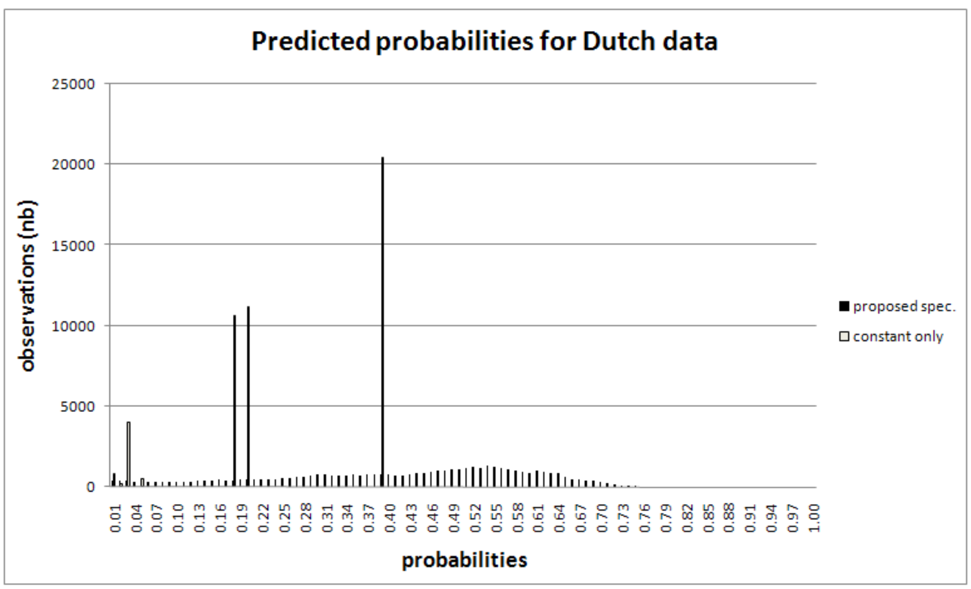
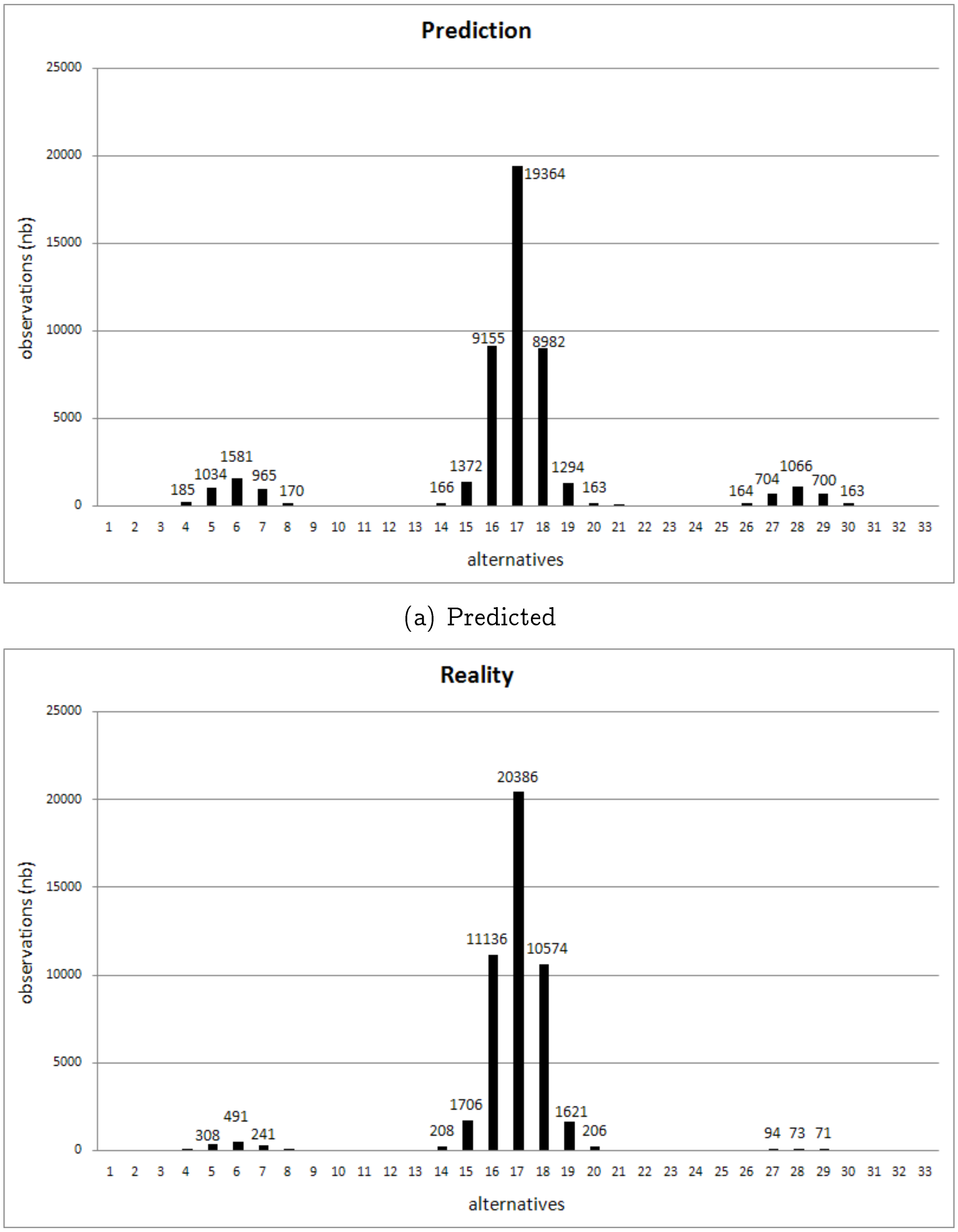


Figure 14: Prediction with the constant-only and proposed model

We now compare the predictions performed by our model with the actual observations. The top part of Figure 15 reports the predicted probabilities obtained by sample enumeration, that is, for each i, $\sum_n P_n(i)$, and the bottom part the observed shares, that is $\sum_n y_{in}$. The predictions are very satisfactory, except maybe for decelerations (alternatives 22 to 33) and accelerations (alternatives 1 to 11).



(a) Predicted

(b) Observed

Figure 15: Choice histogram predicted by the model against revealed choices in the Dutch data set

Cone	Γ	M_Γ	R_Γ	$(M_\Gamma - R_\Gamma)/R_\Gamma$
Front	$5-7, 16-18, 27-29$	43552.36	43374	0.0041
Left	$3, 4, 14, 15, 25, 26$	1948.77	2089	−0.0671
Right	$8, 9, 19, 20, 30, 31$	1853.34	1972	−0.0602
Extreme left	$1, 2, 12, 13, 23, 24$	43.91	27	0.6261
Extreme right	$10, 11, 21, 22, 32, 33$	82.62	19	3.3485

Table 9: Predicted (M_Γ) and observed (R_Γ) shares for alternatives grouped by directions with the Dutch data set.

Area	Γ	M_Γ	R_Γ	$(M_\Gamma - R_\Gamma)/R_\Gamma$
acceleration	$1 - 11$	4022.32	1273	2.1597
constant speed	$12 - 22$	40581.06	45869	-0.1153
deceleration	$23 - 33$	2877.62	339	7.4886

Table 10: Predicted (M_Γ) and observed (R_Γ) shares for alternatives grouped by speed regime with the Dutch data set.

We also perform the comparison at a more aggregate level, for groups of cells. Tables 9 and 10 show a good overall performance of the model. Clearly, the `extreme left` and `extreme right` groups contain too few observations to reach any conclusions. The only bias seems to consist in a systematic over-prediction of accelerations and decelerations. This is consistent with the above-described analysis. The Dutch data set was collected in controlled experimental conditions, which may have introduced a bias in pedestrian behavior, depending on the exact instructions they have received. This assumption is supported by the quasi absence of decelerations in the data set, and by the different shapes of the speed distributions (see Figure 16). While the Japanese curve appears to be Gaussian, the Dutch curves contain some non-Gaussian features which are likely the result of the experimental nature of the data.

Data Set	Mean speed [m/s]
Dutch (experimental)	1.297
Japanese (real)	1.341

Table 11: Average pedestrian speed in the data sets

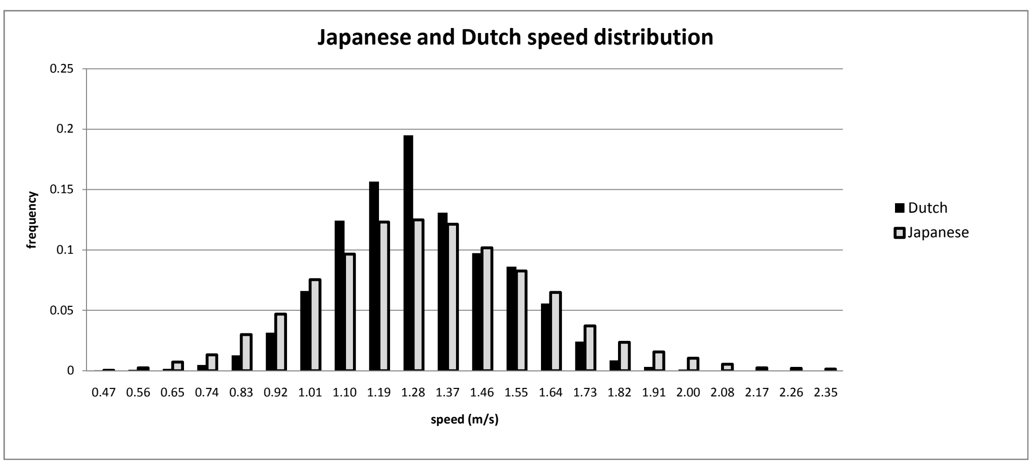


Figure 16: Distribution of speed in the two data sets

We now report the same aggregate prediction obtained with the constant-only model in Tables 12 and 13. The good performance of this simple model at the aggregate level emphasizes the need for the disaggregate validation performed above. Indeed, the relatively good performance of the model is due to the coincidental similarity of proportions of chosen alternatives in the two data sets (see Table 8). The detailed analysis presented in Figure 14 clearly rejects the simple model, while the aggregate analysis does not.

Cone	Γ	M_Γ	R_Γ	$(M_\Gamma - R_\Gamma)/R_\Gamma$
Front	$5-7, 16-18, 27-29$	43386.42	43374	0.0003
Left	$3, 4, 14, 15, 25, 26$	1877.47	2089	-0.1013
Right	$8, 9, 19, 20, 30, 31$	2082.10	1972	0.0558
Extreme left	$1, 2, 12, 13, 23, 24$	51.16	27	0.8947
Extreme right	$10, 11, 21, 22, 32, 33$	81.85	19	3.308

Table 12: Predicted (M_Γ) using the constant-only model and observed (R_Γ) shares for alternatives grouped by direction with the Dutch data set.

Area	Γ	M_Γ	R_Γ	$(M_\Gamma - R_\Gamma)/R_\Gamma$
acceleration	$1-11$	5448.24	1273	3.2798
constant speed	$12-22$	38700.42	45869	-0.1563
deceleration	$23-33$	3330.34	339	8.824

Table 13: Predicted (M_Γ) using the constant-only model and observed (R_Γ) shares for alternatives grouped by speed regime with the Dutch data set.

For the sake of completeness, a constant-only model was calibrated on the Dutch data set, in the same way as for the Japanese. Our model estimated on the Japanese data is better than the constant-only model estimated on the Dutch data, when applied on the Dutch data set, both in terms of log-likelihood (-51303.58 against -71847.69) and prediction (2.41 %, percentage of outliers against 4.33%). We have summarized the various loglikelihood values in Table 14, where each column corresponds to a model, and each row to a data set.

Data set	Our model	Constant-only model based on Japanese data	Constant-only model based on Dutch data
Japanese	-13944.74	-17972.03	—
Dutch	-51303.58	-77269.28	-71847.69

Table 14: Loglikelihood of each model applied to the two data sets

7 Conclusions

In this paper we propose a discrete choice model of pedestrian walking behavior. The short range walking behavior of individuals is modeled, identifying two main patterns: constrained and unconstrained. The constraints are generated by the interactions with other individuals. We describe interactions in terms of leader-follower , and collision avoidance model. These models capture self-organizing effects which are characteristic of crowd behavior, such as lane formation. Inspiration for the mathematical form of these patterns is taken from driver behavior in transportation science, and ideas such as the car following model and lane changing models have been reviewed and re-adapted to the more complex pedestrian case. The difficulties of collecting pedestrian data as well as the limited information conveyed by pure dynamic data sets limit the possibilities in model specification. Important individual effects cannot be captured without the support of socio-economic characteristics. Recent development of pedestrian laboratories (see among others Daamen and Hoogendoorn, 2003a, Nagai et al., 2005, Helbing et al., 2005, Cepolina and Tyler, 2005, Kretz et al., 2006), where controlled experimental conditions are possible, represent an important step in this direction. We use experimental data in a two step validation procedure. First, the model is validated on the same data set used for estimation in order to check for possible specification errors. Second, the model is run on a new data set collected at Delft University under controlled experimental conditions. The proposed validation procedure suggests good stability of the model and good forecasting performance. Few observations are badly predicted, mostly concentrated at the extremes of the choice set. The estimated coefficients are significant and their signs are consistent with our behavioral assumptions. As opposed to other previous models, we can quantify the influence of the relative kinematic characteristics of leaders and colliders on decision-maker behavior. Moreover, such quantitative analysis has been performed using real world pedestrian data.

The validation procedure is rather complete, since it involves several models, including a simple one, and analyzes the results both at an aggregate and a disaggregate level. The next step would be to validate the model within actual tools, such as pedestrian simulators or automatic video tracking systems (Antonini, Venegas, Bierlaire and Thiran, 2006).

Acknowledgments

We are very grateful to Kardi Teknomo and Dietmar Bauer (Arsenal Research) and Serge Hoogendoorn and Winnie Daamen (TU Delft), who provided us with the data sets.

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