Pedestrians choices

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1 Introduction

Among the various modes of transportation, walking is probably the most natural but also the most complicated to apprehend from an analyst viewpoint. Contrary to most other travel modes, it is not associated with a vehicle and the underlying infrastructure is highly heterogeneous (sidewalks, crossings, buildings, shopping malls, squares, etc.) Understanding and predicting the evolution of pedestrians in these various environments is important in many aspects. The first application that comes to mind is the planning of building evacuation in case of emergency, or city evacuation in case of a disaster. Another important application is the description of congestion caused by heavy flows of pedestrians and their conflicting movements. Indeed, it must be accounted for the efficient design of new facilities (such as public buildings, train stations, airports or intersections of urban streets) and the daily operations of these facilities. Focusing on individual behavior in sparse conditions is also important. Among others, travel guidance and information systems aim at helping the pedestrian in implementing her journey, surveillance systems are interested in detecting abnormal behavior, advertisers are interested in evaluating the global exposure of their announcements, movie and video games makers are interested in generating realistic synthetic behavior.

The flourishing scientific literature, as well as the increasing availability of commercial tools, are evidences of the growing importance of this field, but also of its multidisciplinary nature. Indeed, models inspired by physics, artificial intelligence, computer vision, econometrics, biology and traffic flow theory have been proposed.

In this chapter, we consider the models capturing the behavior of individual pedestrians, described in terms of choices. Choice models have been successfully applied to forecast behavior in many instances of travel demand analysis for the past 40 years. Therefore, they immediately come to mind for pedestrian behavior. In Section 2, we identify the types of choices that a pedestrian is confronted to, and describe how each of them has been addressed in the literature. Section 3 summarizes the discrete choice framework and its underlying assumptions, and emphasizes how discrete choice models could be or have been used in this context.

2 Choices of pedestrians

The concept of choice is present in many dimensions of the pedestrian behavior. Although most of these choice dimensions are highly interrelated in reality, and usually considered jointly in the literature, it is more convenient to analyze each of them separately. Let us consider a single individual at a given location at a given point in time.

2.1 Activity choice

A first decision to be made is about what to do next. The choice of the next activity will indeed trigger the travel. This type of choice is not necessarily related to pedestrians, as it is relevant to any travel mode. Among the vast literature, we refer the reader to Jones et al. (1990), Morey et al. (1991), Axhausen and Gärling (1992), Ettema and Timmermans (1997), Kitamura and Fujii (1998), Bhat and Singh (2000), Bowman and Ben-Akiva (2001), Bhat and Koppelman (2004), Abdelghany et al. (2007).

Few authors analyze the activity choice in the specific case of pedestrians. Hoogendoorn and Bovy (2004) distinguish between the choice of an *activity pattern*, performed at a so called "strategic" level, from *activity scheduling*, performed at a "tactical" level, and assume that pedestrians make a simultaneous path-choice and activity area choice decision. Handy (2007) analyzes the impact of the urban form on the choices of the pedestrians in Austin to test if appropriate urban design can discourage automobile dependence. Borgers and Timmermans (1986) consider impulse stops, where the choice of the activity is not planned, but triggered by stimuli in the pedestrian's environment.

2.2 Destination choice

The choice of the destination is related to the choice of the location of the chosen activity. Again, such a choice is not specific to pedestrians, and has been widely analyzed in the literature (Fotheringham, 1986, Fesenmaier, 1988, Woodside and Lysonki, 1989, Furuichi and Koppelman, 1994, Timmermans, 1996, Dellaert et al., 1998, Oppermann, 1999, Scarpa and Thiene, 2005, Bigano et al., 2006 and many others)

With respect to pedestrians, Borgers and Timmermans (1986) develop a destination choice model as part of a system of models to predict the total demand for retail facilities within inner-city shopping areas. Timmermans et al. (1992) provide a review of models existing in 1992 and of a few applications to urban and transportation planning in The Netherlands. Zhu and Timmermans (2005) focus on shopping decision processes, using bio-inspired heuristics to mimic the decision process. Eash (1999) has developed models for non motorized destination choice and vehicle versus non motorized mode choice, with application to the Chicago Area.

2.3 Mode choice

Two types of mode choice are considered in the literature on pedestrian travel. First, the usual transportation mode choice analysis, where walking is one of the alternatives. For instance, Bhat (2000) presents a mode choice model in the Bay Area for work travel. Ewing et al. (2007) analyze travel decision of students going to school. Cervero and Radisch (1996) investigate the effects of New Urbanism design principles on both non-work and commuting travel by comparing modal splits between two distinctly different neighborhoods in the San Francisco Bay Area. Rodriguez and Joo (2004) illustrate the link between mode choice and environmental attributes for commuters to the University of North Carolina in Chapel Hill.

The second type of mode choice focuses on the choice among stairways, escalators or elevators while walking. Several models have been proposed in order to quantify the impact of such elements on the pedestrian behavior. Hamada et al. (2008) are interested in the configuration of a high building , in terms of optimization of floor plan and elevator configuration. Cheung and Lam (1998) reports on the behavior of pedestrians in choosing between escalators and stairways in Hong Kong Mass Transit Railway (MTR) stations during peak hours. Kinsey et al. (2008) propose an escalator model designed for circulation and evacuation analysis, involving microscopic person-person interactions. Toshiaki et al. (2000) compare the choice between the stairs and the escalator for healthy and disabled people. Note that the analysis of this type of choice is of increasing interest for health applications in general, and overweight and obesity issues in particular (Eves et al., 2006).

2.4 Route choice

The choice of the itinerary (or route) is a critical dimension of the pedestrian behavior.

Kurose et al. (2001) analyze the impact of the attractiveness of a street to the route choice in a shopping context. In the same spirit, Borst et al. (2001) describe the relationships between the perceived attractiveness of streets and the (physical) street characteristics. Seneviratne and Morrall (1985) report a study done by the University of Calgary to evaluate the factors affecting the choice of route. They emphasize the importance of distance, while the level of congestion, safety or visual attractions appear to be secondary. Tsukaguchi and Matsuda (2002) combine the street environment, the characteristics of pedestrians and the spatial relationship between the current location and the destination to analyze route choice behavior. Daamen, Bovy, Hoogendoorn and de Reijt (2005) have collected route choice data in two Dutch train stations by following passengers from their origins to their destinations through the facility, and estimated route choice models. Hoogendoorn and Bovy (2004) combine route choice, activity area choice, and activity scheduling using dynamic programming. Okada and Asami (2007) incorporate utility at nodes in a pedestrian flow model, and derive route choice probability using an aggregate logit model. Millonig and Schechtner (2005) proposes a route choice model in the context of pedestrian navigation services.

2.5 Walking behavior: the choice of the next step

The choice of the next step relates to the orientation of the walk, as well as the speed. Muramatsu et al. (1999) and Kessel et al. (2002) propose a so-called "driven" random walk model, where the probability of the next step depends on the number of occupied cells. Cellular automata models are built on a fixed spatial discretization (Blue and Adler, 2001, Burstedde et al., 2001 , Schadschneider, 2002, Dijkstra et al., 2002, Weifeng et al., 2003, Schadschneider et al., 2002, Yang et al., 2002) where transition rates capture the dynamics of the pedestrians. Hoogendoorn et al. (2002) assume that pedestrians follow given trajectories, and can choose among many of them. Therefore, the next step behavior is driven by the current trajectory. Helbing and Molnar (1995) introduce the concept of social forces to describe the motion of pedestrians. Antonini, Bierlaire and Weber (2006) adopt a discrete choice framework for the next step where a dynamic and pedestrian specific spatial discretization is used

2.6 Walking behavior: the choice of the speed

The choice of the speed is captured in different ways depending on the modeling framework. Statistical analysis on real data have been used to derive speed profiles. Knoblauch et al. (2007) focus on crosswalks in urban areas, while Young (2007) collect data in airport terminal corridors. Tarawneh (2001) integrates the effect of age and gender in the analysis. In the context of flow models, the fundamental relationship among speed, flow and densities is the main modeling element (Lam and Cheung, 2000, AlGadhi et al., 2002, Hughes, 2002, Lam et al., 1994, Virkler and Elayadath, 1994). Sugiyama et al. (2002) derive physic models, extending car following models to pedestrians. At a more disaggregate level, Ishaque and Noland (2008) model the pedestrian street crossing movements and speed choice at a micro-scale. Antonini, Bierlaire and Weber (2006) combine the choice of the speed with the choice of the direction using a dynamic spatial discretization.

2.7 Interactions

The interactions among pedestrians play a key role in the analysis of their behavior.

First, group behavior, where individual decisions are influenced by the other members of a group (Goldstone and Janssen, 2005), has been analyzed by several authors. James (1953) and Coleman (1962) analyze the size of the groups, Goldstone et al. (2006) focus on group formation, Was (2008) differentiate active and passive pedestrian behavior within familiar groups, Miyazaki et al. (2003) performed a series of experiments to investigate the behavior of groups of pedestrians and a wheelchair user. Yersin et al. (2008) consider group behavior in real-time crowd motion planning.

Second, the complex self-organization of crowds (Helbing et al., 1998, Helbing et al., 2001, Hoogendoorn and Daamen, 2005, Goldstone and Roberts, 2006), where leader-follower and collision avoidance behavior generate specific patterns have been analyzed extensively. In particular, the spontaneous formation of lanes has been emphasized (Helbing and Molnar, 1995, Blue and Adler, 1999, Burstedde et al., 2001, Dzubiella et al., 2002). Collision avoidance and leader follower behavior have been specifically analyzed and modeled in various contexts (Loscos et al., 2003, Daamen and Hoogendoorn, 2003b, Sakuma et al., 2005, Pelechano and Badler, 2006, Robin et al., 2009).

The interactions with the environment are also important. Daamen et al. (2002) account for the entire picture of the scene in their models. Nagel (2002) includes walking in traffic simulations. Helbing et al. (1998) propose the 'active walker' model that takes into account pedestrian motion and orientation and the concomitant feedbacks with the surrounding environment. Dijkstra and Timmermans (2002) use a multi-agent model to derive several performance indicators of building environments, which are related to user reaction to design decisions. Guo and Ferreira (2008) illustrate how the quality of pedestrian environments along transit egress paths affects transfers inside a transit system, and how the impedance of transferring affects egress walking path choices. Zacharias (2001) is interested in assumptions about how pedestrians respond to characteristics of the environment as they formulate and enact their walking itineraries.

Finally, the interactions between pedestrians and drivers are relevant as a major safety issue (Himanen and Kulmala, 1988, Tidwell and Doyle, 1995).

2.8 Pedestrian data

We conclude this section by describing various types of data that are collected to analyze pedestrian behavior.

Questionnaires and "manually" collected data have been used in many studies, to obtain behavioral data (Sisiopiku and Akin, 2003) or counts (Cunningham and Cullen, 1993). But data collection using technology is more and more common in various research communities interested in pedestrian behavior.

Pedometers have been used mostly in the context of health research programs. Whitt et al. (2004) combine pedometer and physical activity reports to analyze walking patterns. Bassett et al. (2000) report that subjects underestimated their daily walking distance in a survey compared to the pedometer record. Bennett et al. (2007) use pedometers to analyze the relation between walking and the perception of safety.

Location based-services provided namely by cell-phones generate relevant data. Sohn et al. (2006) use GSM traces for mobility detection, Ratti et al. (2006) analyze the potential of cell-phones location-based services to the urban planning community, and Li (2006) uses location-based services to analyze pedestrian wayfinding behavior. Millonig and Gartner (2009) combine qualitative-interpretative and quantitative-statistical data leading to the determination of a typology of lifestyle-based pedestrian mobility styles.

The next obvious important data collection system is the Global positioning system (GPS). For instance, Liao et al. (2007) use GPS data to calibrate activity and location choice models, as well as Ashbrook and Starner (2003) who also consider collaborative scenarios. Patterson et al. (2003) derives the current transportation mode and the most likely route of a traveler from GPS data. Shoval and Isaacson (2006) review the use of satellite navigation systems and land-based navigation systems for gathering data on pedestrian spatial behavior. Flamm and Kaufmann (2007) propose a survey design combining GPS-based person tracking and qualitative interviews to understand behavioral changes occurring during life course transitions.

There is also an increasing interest in exploiting video sequences of pedestrians within urban or building areas. In this context, two types of data are considered: counts and trajectories. Pedestrian head counts are useful to calibrate flow models whereas pedestrian trajectories are used for the estimation of disaggregate models.

Several computer vision algorithms have been designed for counting pedestrians. Sexton et al. (1995) propose an image processing counting algorithm in unconstrained areas. Zhang and Sexton (1997) combine a model-specified directional filter with a matching process to count pedestrians against a dynamic background. Chen (2003) propose an automatic bi-directional pedestrians counting method through gates.

With respect to pedestrian trajectories, Teknomo et al. (2000) collect data on a real pedestrian crossing road in Sendai, Japan. Daamen and Hoogendoorn (2003b), Daamen and Hoogendoorn (2003a) and Daamen (2004) provide videos of experimental pedestrian trajectories of volunteer pedestrians performing walking tasks in controlled configurations. Several parameters are considered such as free speed, direction, density and bottlenecks. Trajectories are extracted from video sequences, by using computer vision algorithms. Teknomo (2002) and Hoogendoorn et al. (2003) developed specific pedestrian tracking methods, Sullivan et al. (1995) use active deformable models for the same purpose. Masoud and Papanikolopoulos (1997) and Denzler and Niemann (1997) present real-time systems to track pedestrians in video sequences. Antonini, Venegas, Bierlaire and Thiran (2006) propose a framework combining state-of-the-art detection and tracking methodologies with behavioral models.

3 Discrete choice models

Discrete choice models (McFadden, 1981, Ben-Akiva and Lerman, 1985, Train, 2003) have been widely applied in the context of travel decisions (Ben-Akiva and Bierlaire, 1999). Disaggregate in nature, these models are based on random utility theory. We consider a decision-maker n who is performing a choice among a set $\mathcal{C}_n$ of J_n alternatives. It is assumed that n associates a utility U_{in} to each alternative i within $\mathcal{C}_n$, and selects the alternative corresponding to the highest utility. The utility is modeled as a random variable to account for uncertainty due to various issues, including unobserved variables and measurement errors. The utility is decomposed into a deterministic part V_{in} and an error term ε_{in}, so that

$$U_{in} = V_{in} + \varepsilon_{in}, \tag{1}$$

and the probability that individual n is selecting alternative i is

$$P_n(i|\mathcal{C}_n) = \Pr(U_{in} \geq U_{jn}\ \forall j \in \mathcal{C}_n). \tag{2}$$

Operational models are derived from explicit specifications of V_{in} and distributional assumptions about ε_{in}.

The specification of V_{in} includes the selection of the explanatory variables, that is the attributes of i relevant to n, as well as the socio-economic characteristics of n. A functional form used to compute the utility from these variables must also be assumed. The distributional assumptions determine the complexity of the model. The most widely used model is the *logit model*, which assumes that the ε_{in} are independent across both i and n, and identically distributed with an extreme value distribution, leading to a simple and tractable formulation. The more complex models such as the nested logit (Ben-Akiva, 1973, Williams, 1977, Daly and

Zachary, 1978), the multivariate extreme value (McFadden, 1978), the probit model (Thurstone, 1927) or the mixture of logit models (McFadden and Train, 2000) are designed to relax these assumptions that may be unrealistic in some contexts.

In the following, we review how discrete choice models have been or could be applied to model the various choices described in Section 2, focusing on the features specific to pedestrians. Most of the time, we raise issues instead of providing solutions. The objective is to stimulate new ideas and new potential models.

3.1 Activity choice

Traditional travel demand analysis focus on the schedule of activities, where the choice of activity patterns is modeled (Bowman and Ben-Akiva, 2001). Due to the combinatorial nature of the choice set, operational models focus on scheduling the most important activities, such as *stay home*, *work*, *school* and *shopping*. The analysis of pedestrian movements require a more detailed analysis of activities, where the set of considered activities must be refined, and the choice of the next activity to be performed by a pedestrian at any point in time is relevant. For instance, on her way back home from work, a pedestrian may choose between rushing to catch the train, or having a coffee and taking the next train. Clearly, this decision will have significant impacts on her walking behavior, and may therefore be important to model. Impulse stops are another typical example, where the choice of the next activity is triggered by various stimuli in the environment. This is particularly relevant for shopping (Borgers and Timmermans, 1986) and tourism (Stewart and Vogt, 1997) activities, where individuals can easily be diverted from their original plans.

Several challenges are associated with the derivation of a choice model for the next activity. As discussed above, the characterization of the choice set is highly context-dependent, and the list of the activities that may be potentially considered is not always available to the analyst. Moreover, walking may be a potential activity as such.

With respect to the explanatory variables, the location of an activity plays an important role. Consequently, it is natural to combine the activity choice model with the destination choice model, as discussed below. Variables describing the design of existing stimuli (e.g. type and size of an advertisement) are also important. Variables capturing the importance of activity providers can also be considered. Borgers and Timmermans (1986) use the retail turnover, the average per capita expenditure and the turnover to floorspace ratio of a category of stops to explain impulse stops. Contextual variables, such as the time of day (Dellaert et al., 1995) and the weather conditions may also play an important role. Finally, several relevant socio-economic characteristics should be considered, such as gender (Jansen-Verbeke, 1987), age, or type of household (Krizek, 2006).

Due to the context-specific nature of pedestrian activity choice models, no general recommendation can be made for the distributional assumptions of the error terms, although it is likely that a simple logit model may not be appropriate for many instances due to unobserved attributes shared by several alternatives.

3.2 Destination choice

Influenced by traditional practice in travel demand analysis, several models are derived from origin-destination matrices (Nagel and Barrett, 1997, Antonini, Bierlaire and Weber, 2006), where the set of potential origins and destinations is predefined, and flows between origins and destinations is estimated. In a disaggregate context, the choice of the destination can be modeled conditional to a given activity, or as a joint choice of an activity and a destination. In both cases, the choice set is typically large and difficult to characterize. The size of the choice set depends on the application. For example, in a building, the number of possible exits is usually not huge. But in a shopping mall or a city center, the number of possible destinations or intermediate stops, can be extremely large. It is good practice to sample alternatives out of the full choice set to derive operational models. If a logit or a multivariate extreme value model is used, efficient estimators using samples of alternatives are available (Manski and Lerman, 1977, Bierlaire et al., 2008).

In addition to the variables describing the attractiveness of a destination, it is particularly important to also account for distance. Moreover, the impact of distance on the choice usually interacts with socio-economic characteristics of the pedestrian, such has age, sex, possible disabilities, etc. Also, the number of other activities that may potentially be performed at a destination will influence the choice, as illustrated by the attractiveness of commercial centers or leisure parks.

The error structure of destination choice models can be complex. First, if we are considering the joint choice of an activity and a destination, we are dealing with a multidimensional choice set where alternatives are correlated by construction. If nested logit models have been historically used to handle part of the correlation in multidimensional choice sets (Ben-Akiva and Lerman, 1985, chapter 10), mixture of logit models provide a more accurate representation of the correlation (Bhat, 1998), although at the cost of higher complexity. Second, destination choice include a spatial dimension, and the associated spatial correlation should be accounted for in the model (Fotheringham, 1986). A typical example for pedestrians is when two doors are close to each other, or give access to the same room or the same street. Bhat and Guo (2004) suggest to account for the correlation among neighboring destinations, and use a cross-nested logit to capture it.

We conclude this section by noting that, in some circumstances, it may happen that no destination is explicitly chosen by a pedestrian. It is typical when walking is the activity as such, or in shopping and touristic activities. In these cases, an itinerary is chosen without a known target, trying to maximize the chances to reach attractive places along the way (Borst et al., 2001). This type of behavior is clearly difficult to formalize, and is closely linked with the route choice behavior.

3.3 Mode choice

Mode choice models are probably the most traditional discrete choice models. As discussed above, two types of mode decision can be considered. There is not much to discuss about the standard mode choice where walking is one of the alternatives.

With respect to the use of mechanized devices such as elevators, escalators, we first note that it is intrinsically related to route choice behavior (Daamen, Bovy and Hoogendoorn, 2005). Focusing on the mode choice, the choice is typically small, as less than a handful of alternatives is in general available to change levels. With respect to explanatory variables, Cheung and Lam (1998) include expected delays in congested situations, Nicoll (2006) includes the visibility of stairs, the “imageability” (Lynch, 1960), that is quality in a physical object which gives it a high probability of evoking a strong image in any given observer (typically, the type of stairs, the type of elevator, etc.), the intelligibility of the environment, characterized for instance by the number of turns to reach the stairs, the setting appeal, that is the value of the view when using the stairs or the elevators. Comfort and safety variables can also be envisaged. Foster and Hillsdon (2004) consider the possible impact of health campaigns stimulating the use of stairs, but they did not find significant evidence of their impact in their studies.

The structure of the error term for these models should be similar to traditional mode choice models, where the logit model is usually appropriate.

3.4 Route choice

Route choice models are traditionally based on a network structure (Bovy and Stern, 1990, Ramming, 2001, Frejinger, 2008). In the pedestrian context, there is no physical network infrastructure associated with the movements of the individuals (Hoogendoorn and Bovy, 2004). Within a discrete choice framework, two approaches can be considered.

A first possibility is to design a virtual network structure. The nodes would correspond to the key decision points (doors, intersections of corridors, crossways, stairs, elevators, etc.), and the links would connect adjacent nodes. Note that such a network would typically be denser than a road network, as a great deal of nodes may be necessary in the presence of large spaces. Also, it must not be assumed that the pedestrians will exactly follow the link of this virtual networks, and the associated walking model must be designed accordingly. Network-free model estimation, as proposed by Bierlaire and Frejinger (2008), is then necessary. When the virtual network is defined, the usual complexities of route choice models must be addressed, including the very large size of the choice sets (Frejinger, 2007) and the high structural correlation among the paths (Frejinger and Bierlaire, 2007).

Another possibility would consist in assuming a more myopic behavior of the pedestrians, where they would choose the next intermediary point on their way to the destination. The set of possible intermediary points can be constructed similarly to the nodes of the virtual network mentioned above, but may also be dynamically updated as the pedestrian moves and discovers her environment.

Compared to a network-based approach, the choice set contains the list of potential intermediary stops, which has no combinatorial dimension. The variables describing each of them should reflect not only the location of the place itself, but also all the elements that will be met on the way to it. This is where a combinatorial dimension may increase the complexity of the model. However, this can be controlled by excluding from the choice set the alternatives which are quite distant from the current location, so that the number of elements in between is bounded. The choice set can then be updated dynamically as the pedestrian moves.

Inspired by the walking model proposed by Antonini, Bierlaire and Weber (2006), and by suggestions from Fosgerau to address the complexity of traditional route choice models, this modeling scheme have several advantages. Structurally less complex than network-based approaches, it may also be appropriate as a basis to derive models capturing phenomenons such as impulse stops.

The spatial dimension of this choice would suggest an error structure based on mixtures of logit models, with error components explicitly capturing the correlation. If the size of the choice set is too large, multivariate extreme value models may be more appropriate, where the operational representation proposed by Daly and Bierlaire (2006) should be considered, together with sampling of alternatives (Bierlaire et al., 2008).

3.5 Walking behavior: the choice of the next step

The choice of the next step is central in the pedestrian modeling. It represents the instantaneous decision, and implies a lot of factors. In this context, Antonini, Bierlaire and Weber (2006) propose a discrete choice model where the pedestrian visual space is discretized in a set of possible next steps, corresponding to the choice set. It is dynamic, evolving with the individual's current speed and direction. The choice set is multidimensional, combining three acceleration patterns (deceleration to 0.75 times the current speed, same speed, and acceleration to 1.25 times the current speed) with 11 possible directions. While the discretization of directions is relatively straightforward and natural, the discretization based on acceleration patterns can be done in several ways, as discussed in the next subsection.

The choice set could be adapted to the environment. For example on a straight and large side-walk, the number of considered direction could be decreased, if pedestrians are unlikely to make significant changes of direction. It could also be adapted to pedestrian characteristics, such as age, sex, height, visual angle, trip purpose, or group membership. Crassini et al. (1988) performed visual experiments comparing young and elderly people and quantitatively measured the perceptions differences.

The utility function associated with a given alternative, that is with a given combination of location and acceleration, must capture various behavioral patterns. Speed and interaction patterns are discussed in the following subsections. Two orientation patterns must also be considered. The first captures the propensity of pedestrians to keep their current direction, following a smooth and regular path. This is consistent with the findings of Turner (2001) who provide angular analysis of walking environments such as buildings. The second captures the attraction of the destination, consistently with Helbing et al. (2002) who state that pedestrians want to reach as fast as possible their destinations in non crowed situations. Therefore, alternatives allowing the pedestrian to move closer to the destination should have a higher utility. Antonini, Bierlaire and Weber (2006) and Robin et al. (2009) include the angle between the direction d_i associated with a given alternative i and the current direction to capture the first pattern. They also include the angle between d_i and the direction towards the destination for the second pattern, as well as the distance between the position of the next step and the destination.

The multi-dimensional nature of the choice set induces structural correlation among the alternatives, which suggests the use of a cross nested logit (CNL) model (Bierlaire, 2006) or an error component model (Walker et al., 2007). Moreover, the typical panel nature of the data, where the same individual is observed over time, suggests the presence of unobserved heterogeneity which should be modeled using an error component distributed across the population and not across the observations (Train, 2003, Section 6.7).

3.6 Walking behavior: the choice of the speed

Speed modeling can be considered in two ways. We described above how it can be integrated in the “next step” model. A second approach consists in considering the choice of the speed independently from other walking decisions. In both cases, there are typically two ways of defining the choice set. It can be a list of possible absolute speeds, ranging from 0 to the maximum possible speed that can be achieved by a pedestrian, discretized in some appropriate way. Although they do not use a discrete choice framework, Blue and Adler (1998) adopt a similar approach in a cellular automata context. Wakim et al. (2004) consider "standing still", "walking", "jogging" and "running" in a Markov chain process. It can also be a list of possible modifications relative to the current speed. These modifications can be defined in absolute terms (e.g. $+\ 0.1$m/s) or in relative terms (e.g. $\times$ 1.10). The former model is more natural, but must integrate mechanisms avoiding unrealistic variations in speed.

Many variables may explain the speed behavior and can be included in the model specification. The first set of variables is directly inspired from macroscopic flow theory, where the relationships between flow, density and speed of pedestrians are characterized. Therefore, current density, flow or combination of the two should be integrated as explanatory variables. Kessel et al. (2002) propose a microscopic model based on the fundamental relation between walking speed and crowd density. Seyfried et al. (2005) analyze experimentally the microscopic causes of the velocity decrease in the presence of medium or high densities, such as frequency of passing manoeuvres and internal crowd frictions. Also, pedestrians characteristics, such as age, height, sex, trip purpose influence the velocity. For instance, Coffin and Morrall (1995) analyze the speed behavior of elderly people on crosswalks in order to improve such infrastructure in occidental aging societies.

The pedestrian environment is of course predominant in the speed choice process. An arriving train, a traffic light turning to red while in the middle of the crosswalk, or the presence of a slow group of people are events that trigger change of speeds.

Among the possible speeds that a pedestrian may select, the zero speed has a different nature and must be treated separately. The variables explaining the choice of a zero speed may be different from the variables explaining another speed regime. For instance, the presence of an impassable obstacle, the sudden perception of a danger or the occurrence of various external stimuli (traffic light, advertisements, etc.) may cause a pedestrian to stop.

It is important also that the speed model is able to manage restarts after stops. For instance, if the choice set is defined based on relative modifications of the current speed (e.g. $+10\%$), it is obviously not appropriate to model the restart. Also, if an impassable obstacle fills in the visual field of a pedestrian, the restart cannot occur before the direction is updated, clearing the visual field.

Finally, the speed may be influenced by the various interactions discussed below (group behavior, leader-follower, collision avoidance).

Depending on the nature of the choice set, the type of correlation between the error terms may vary, but it is seldom the case that independence can be safely assumed. Indeed, among the possible speed changes, the error terms of all alternatives corresponding to an acceleration are likely to be correlated, as well as the error terms of all alternatives corresponding to a deceleration. If the choice set contains a list of absolute speeds, two consecutive values are likely to be perceived more similar than two different values. In this case, models similar to departure time choice model (such as the Ordered GEV model by Small, 1987, which is a special instance of a CNL) are appropriate. Clearly, more complex MEV models, as well as error component models are relevant here as well.

3.7 Interactions: group behavior

Group behavior relates to the adjustment of individual behavior to comply to groupwise behavioral patterns. It can be motivated by behavioral affinities (fast people passing slower individuals in a dense crowd), social links among individuals, such as friends or relatives or simply fortuitous spatial proximity.

Assuming that the groups are clearly and unambiguously identified (which is by itself a challenge, as groups can split or merge dynamically), there are two ways of modeling this behavior. First, the decision-maker can be considered as the group itself, and its various moving decisions are modeled as a joined choice accounting for the larger physical space occupied by the group. It is similar to the concept of "packets" used in traffic simulation (Ben-Akiva et al., 1994, Cornélis and Toint, 1998). Second, the group characteristics, such as size, type or speed, can be considered as exogenous to the model describing the choices of a specific member of the group. Clearly, the two models can be merged in a two stages framework, where the group behavior is modeled at the higher level, and the individual behavior is modeled conditional to the group's.

Note that in addition to the moving behavior, the decision for a given individual to belong to a group can also be modeled in a discrete choice framework, where behavioral, social and spatial similarities are typical explanatory variables.

3.8 Interactions: leader-follower

A leader-follower model capture the propensity of an individual to adjust (consciously or unconsciously) her speed and direction to another individual in order to make her way through a crowd. A similar type of behavior can be modeled in an emergency context, where trained employees may serve as leaders in an evacuation procedure (Pelechano and Badler, 2006).

Two types of choice can be modeled. First, the choice of a leader (or the decision not to follow anybody) is influenced by the characteristics of the surrounding crowd (density, speed, etc.) as well as the behavior of the potential leaders. Pedestrians in the visual field, and with behavior close to the desired target, particularly in terms of desired speed and direction, are more likely to be considered. In the literature, the deterministic choice of the nearest potential leader has been proposed by Blue and Adler (1999) and Robin et al. (2009), suggesting that the distance would be an important explanatory variable in a discrete choice model.

The second type of choice is the reaction to the leader's behavior. Robin et al. (2009) suggest an impact of the leader on the choice of the speed and the direction. Other choices, such as route or even destination can also potentially be affected by the leader's behavior.

The estimation of such models is complicated because the choice itself is not really observed, and can only be guessed by the analyst. It should be modeled as a latent construct.

Note that a great deal of insights can be derived from driving behavior models (Toledo et al., 2007) where car-following (Chandler et al., 1958) and lane changing (Ahmed et al., 1996) models play a key role.

3.9 Interactions: collision avoidance

Instead of being attracted by another individual, and positively influenced, a pedestrian in a collision avoidance context is repelled and negatively influenced by somebody else.

While the impacts themselves on the speed and direction are clearly different, the process of identifying the individual to avoid can be modeled with a discrete choice framework, in a way similar to the selection of the follower described above. As before, the identification of a potentially colliding individual is influenced by the characteristics of the surrounding crowd (density, speed, etc.) as well as the behavior of that person. Pedestrians in the visual field with speed and direction suggesting a possible collision are more likely to be considered in the choice set. Robin et al. (2009) select the “candidate” such that the angle of the two directions is the closest to π, suggesting that the angle would be an important explanatory variable in a discrete choice model. Also, the distance and the speed are important variables, as they characterize the imminence of the collision.

3.10 Interactions: other scene elements

During the walking process, individuals have to interact with various elements of the scene, such as cars (on crossing road), side-walk environment, or even isolated obstacles. Again, we distinguish between what elements influence the behavior, and how.

On crossing roads, pedestrians interact with cars. Himanen and Kulmala (1988) propose a discrete choice framework to model interactions between drivers and pedestrians on crossing roads without traffic lights. Pedestrian could pass or stop , and drivers brake or weave. The explanatory variables of their model are the number of pedestrians simultaneously crossing, the city size, the vehicle speed and the vehicle size.

The crossing road modeling can be extended and adapted to the interaction between pedestrians and potentially dangerous elements of the scene, such as parking exits, or streetcar lines. Still, the pedestrian chooses between passing, stopping or getting around (not always available). The choice is influenced by the pedestrian characteristics, such as determination, or by the level of danger (characterized, for instance, by the vehicle speed). Evans and Norman (1998) reports a study on the pedestrians road crossing intentions based on the theory of planned behavior. Questionnaires with several crossing manners and scenarios were proposed to respondents. The perceived control of the situation appears to be crucial in the decision making process.

Corners are present at crossings, either implying corridors or side-walks. Those immobile scene elements can increase the likelihood of pedestrian collisions, due to lack of visibility. Different options can be combined by the pedestrian to anticipate such collisions, such as move away from the wall to improve the visual perception, or decelerate (or even stop) at the crossing to check if there is any potential collider. Many factors influence these decisions such as the pedestrian prior experience and characteristics (age, gender, etc.), crowd density, crossing geometry such as angle between corridors or visibility.

Visual advertisements such as posters, screens or shop windows are designed to attract pedestrians' attention. The walker can choose to stop in order to improve her knowledge of the displayed elements, to slow down to glance at it, or to ignore it and continue walking. Attraction must be included in the next step choice model and speed choice model, in order to account for the walking changes due to the advertisement. The stop decision should be considered independently. In addition to the pedestrian's socio-economic characteristics, her current activity and destination, as well as her prior experience with the elements on display influence the choice. The visual attributes of the poster are also crucial. For example, Kerr et al. (2001) perform several experiments in stations and shopping centers, to test the influence of health promotion posters on the pedestrian choice between stairs and escalators. They show that posters size and message have a high influence on the individual perception. In addition, other attributes of the visual form, such as color, or location should also be considered.

Doors are common in public spaces. A standard transparent door is an obstacle that produces only sporadic speed decrease in free-flow-conditions. In the presence of high densities, notion of priorities have to be considered. If a dense crowd tries to pass through the door in one direction, and a single pedestrian tries in the other direction, the latter has a tendency to let pass the crowd. Several meanings of 'let pass' can be considered. Indeed the pedestrian can anticipate the interaction by decreasing her speed, or modify her trajectory and speed, or even stop at the door. This decision can be modeled in a discrete choice framework. Crowd density, door characteristics, such as dimension and type, and pedestrian characteristics influence the choice (Daamen et al., forthcoming).

Side-walks are full of little elements such as benches, trees, garbage cans or streetlights. They could possibly be modeled as static pedestrians, so that the interactions issues described before are applicable. But they can also be considered independently, because of their specificities, such as associated danger. Pedestrians have several possibilities to avoid collisions with those elements: go round by the left, or by the right, stop or turn back. The crowd density is crucial to deal with this decision, as well as pedestrian characteristics.

4 Conclusion

Pedestrian behavior is a complex and important phenomenon. Capturing and forecasting it require advanced modeling and simulation tools. We have tried here to analyze various behavioral dimensions in terms of choice. Not only this is a standard approach in travel demand analysis, but the availability of operational models, such as discrete choice models, justifies to investigate the behavior from the choice viewpoint.

We conclude from this discussion that, if indeed many behavioral dimensions of pedestrian can be considered as choices (as detailed in Section 2), deriving operational models for these choices can be quite complex. The most important reason is that most of these choices are performed at the same time, and a decomposition into a sequence of choices is often not appropriate. The "four-step" approach adopted in travel demand analysis, where travel behavior is decomposed into location choice, destination choice, mode choice and route choice, cannot be applied for pedestrian without major adjustments. Consequently, the complexity of the corresponding models may preclude their use in real applications. A second reason is the short lifetime of some of the choices, as decisions associated with the destination, the route or even with the activity itself are subject to frequent changes. Consequently, the dynamic of the choices must be accounted for. A third major issue is the availability of appropriate data. Although recent developments in GPS data collection and video image analysis have allowed for the modeling of some complex behavioral dimensions, the detailed observation of pedestrian behavior is still a very complex issue.

In summary, we believe that investigating pedestrian behavior in terms of choice behavior is an exciting field of research, with many open issues and a high potential. We hope that this document will stimulate research in this direction.

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