UNIVERSIDADE FEDERAL DO RIO GRANDE DO SUL
ESCOLA DE ENGENHARIA
PROGRAMA DE PÓS-GRADUAÇÃO EM ENGENHARIA DE PRODUÇÃO

Bruno Rocha Werberich

PEDESTRIAN SIMULATION: A ROUTE CHOICE MODEL TO ASSESS URBAN ENVIRONMENTS

Porto Alegre

2017

Bruno Rocha Werberich

Pedestrian Simulation:

A Route Choice Model to Assess Urban Environments

Tese submetida ao Programa de Pós-Graduação em Engenharia de Produção da Universidade Federal do Rio Grande do Sul como requisito parcial à obtenção do título de Doutor em Engenharia, na área de concentração em Sistemas de Transportes.

Orientadora: Helena Beatriz Bettella Cybis, *Ph.D*.

Porto Alegre

2017

Bruno Rocha Werberich

Pedestrian Simulation:

A Route Choice Model to Assess Urban Evironments

Esta tese foi julgada adequada para a obtenção do título de Doutor em Engenharia e aprovada em sua forma final pelo Orientador e pela Banca Examinadora designada pelo Programa de Pós-Graduação em Engenharia de Produção da Universidade Federal do Rio Grande do Sul.

Prof. Orientadora Helena Beatriz Bettella Cybis, *Ph.D*.

Orientadora PPGEP/UFRGS

Prof. Flávio Sanson Fogliatto, *Ph.D*

Coordenador PPGEP/UFRGS

Banca Examinadora:

Professor Michel José Anzanello, Dr. (PPGEP/UFRGS)

Professor Carlos Oliva Pretto, Dr. (UFPel/RS)

Professor Rosaldo José Fernandes Rosseti, Dr. (FEUP/PT)

AGRADECIMENTOS

Agradeço, com muita consideração, a algumas pessoas pela contribuição na construção deste trabalho:

À minha orientadora, Prof.a Helena Cybis, pela orientação, pela disponibilidade e pela confiança depositada neste trabalho.

Ao colega Carlos Pretto pela participação ativa e pelas contribuições fundamentais ao desenvolvimento da pesquisa.

À toda minha família, especialmente ao meu pai Luis Carlos, minha mãe Sandra, e minha namorada Belisa, por apoiarem a minha formação acadêmica e profissional.

À UFRGS e ao PPGEP, aos professores, funcionários e colegas, por proporcionarem o desenvolvimento da pesquisa.

À CAPES e ao CNPq pelo apoio financeiro concedido através de bolsa de estudos.

ABSTRACT

The design of new facilities - buildings, shopping centers, public transport stations, airports, or intersections of urban roads - should consider delays resulting from intense pedestrians' flows in order to make its' operation more efficient. The general objective of this doctoral thesis is to propose a simulation model to represent pedestrians' behavior in urban environments. Simulation models should allow planning these environments in order to provide greater levels of comfort and safety for the pedestrian. Agent-based abstraction has been widely used for pedestrian modeling, mainly due to its capacity to represent complex entities. Agent-based models represent agents' decision-making ability based on their profile and perception over the environment. One of the most important pedestrians' activities is the route choice. This document describes the development of a route choice model based on friction forces. The route cost calculation considers a balance between distance and the impedance generated by other pedestrians. Simulations runs shown that pedestrians choosing longer routes can have similar or better travel times. The ability of choosing not only the shorter route brings more realistic behaviors for the pedestrians' representation, especially with small differences in route lengths and higher congestion. On the proposed model agents were modeled with partial knowledge of the network conditions. The knowledge was limited considering the pedestrian estimated field of view. In the real world it is not possible to know the network state before turning the corner. The model was validated and calibrated with real data. Calibrating a pedestrian route choice model is a complex task mainly for two reasons: (i) Many factors interfere on pedestrians' route choice; (ii) data collection is difficult. To overcome these difficulties real pedestrians were studied in a controlled environment. An experiment was set up inside the university campus. After the calibration process the model was able to simulate a real scenario. Proposed model was applied to simulate a shopping mall environment. Simulate the pedestrians shopping behavior is particularly complex once route choice in shopping malls may be defined by a number of causal factors. Shoppers may follow a pre-defined schedule; they may be influenced by other people walking, or may want to get a glimpse of a familiar shopping. Analysis from simulations indicates that the agents' behavior provides a promising approach for real case applications.

Keywords: Pedestrians Simulation, Pedestrians Behavior, Route Choice

TABLE OF FIGURES

Chapter 1 - Introduction

Chapter 2 – First Paper (*Pedestrian Route Choice Model Based on Friction Forces****)***

Chapter 3 – Second Paper (*Pedestrians' Route Choice Based on Friction Forces Assuming Partial and Full Environment Knowledge****)***

Chapter 4 – Third Paper (*Calibration of a Pedestrian Route Choice Model With a Basis in Friction Forces****)***

Chapter 5 – Fourth Paper (*Following a route: a force field generated from a sequence of points on the plane****)***

Chapter 6 – Fifth Paper (*Pedestrians' Route Choice Model for Shopping Behavior****)***

Chapter 7 - Conclusion

TABLE OF TABLES

Chapter 2 – First Paper (*Pedestrian Route Choice Model Based on Friction Forces****)***

Chapter 6 – Fifth Paper (*Pedestrians' Route Choice Model for Shopping Behavior****)***

TABLE OF CONTENTS

1. INTRODUCTION

Walking is probably the most natural mode of transportation. However, from the point of view of transportation engineering, walking is considered the most complex mode to be modeled since pedestrians are not associated with any vehicle. In addition, the walking infrastructure is extremely heterogeneous, involving sidewalks, intersections, buildings, shops, squares, etc.

One of the most common uses of pedestrian models is the building evacuation planning in case of emergency. Another important application is the simulation of congestion caused by the intense conflicting flow of pedestrians.

The design of new facilities - buildings, shopping centers, public transport stations, airports, or intersections of urban roads - should consider delays resulting from intense pedestrians' flows in order to make its' operation more efficient. Pedestrians are the most vulnerable users of road transport networks, and their increased vulnerability may be attributed by the lack of speed, mass and protection, compared to other road users. And also their particular characteristics like flexibility, ample space requirements and diversity of attention.

Therefore, focus on individual's pedestrian behavior is important to identify variables of interest to pedestrian modeling. Many knowledge areas have different interests in pedestrians modeling. Marketing and Advertising researchers are interested in evaluating the overall exposure of ads and the route used by consumers in large shopping centers. Filmmakers and computer games are interested in representing character behavior realistically through computer graphics processes.

1.1 Theme and importance

Agent-based abstraction has been widely used for pedestrian modeling, mainly due to its capacity to represent complex entities. Agent-based models represent agents' decision-making ability based on their profile and perception over the environment.

An agent is anything capable to perceive the environment through sensors and also capable of acting on this environment through actuators. Usually, the coordination of behaviors in a community of agents is decentralized. This coordination occurs from the integration of knowledge, ability, objectives and plans of the different agents. Agents act autonomously in their decisions over their own actions. Generally, there is no global planning guiding the modeled entities.

Multi-agent systems allow modeling the behavior of a set of entities organized according to laws of the social type. These entities, or agents, have autonomy and are immersed in an environment with which they need to interact. In this way, agents must have a partial representation of this environment and means of perception and communication with it.

Pedestrians' agent behavior is not simply determined by preferences, intentions, desires but by the environment which reflects the spatial or geometric structure in which the agents are inserted. The variability between agents, in terms of their intrinsic differences and the uncertainty that they have to deal with is the most important characteristics of multi-agent systems.

The modeling of pedestrian's agent behavior begins with the understanding of its decision-making process. In Papadimitriou et al. (2009) [1], pedestrian activities are classified into three levels: Strategic, Tactical and Operational, according to Figure 1. In this structure, the strategic level corresponds to travel starting time choice and activity planning. At the tactical level, the route choice and activities scheduling. The operational level corresponds to crossing behavior, sense end avoidance of obstacles and the interaction with other pedestrians.

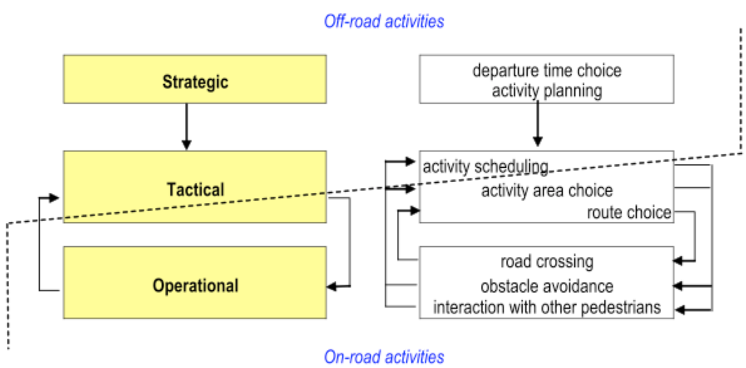


Figure 1- Pedestrian decision levels - Source: Papadimitriou *et al.* (2009) [1]

The modeling of pedestrian agents should not necessarily comprise all decision levels. The complexity of the agent must be suitable to the complexity of the simulated phenomenon. Crowd simulation and evacuation often do not require too much complexity of the agent because simplifications are possible, such as grouping pedestrians with identical goals and objectives, making it not necessary to model the strategic decision level of the agent. Model simplifications save computational resources and consequently allow the simulation of larger scenarios and populations.

1.2 Objectives

The general objective of this doctoral thesis is to propose a simulation model to represent pedestrians' behavior in urban environments. The model should allow planning these environments in order to provide greater levels of comfort and safety for the pedestrian. Specific objectives are:

A) Develop a route choice model for pedestrians considering pedestrians, their profiles and their interaction with the environment and other pedestrians.

B) Understand how pedestrians with different levels of knowledge about the network state affect simulation results.

C) Observe real pedestrians and collect data to reproduce observed behaviors in simulation.

D) Propose a mathematical model of route smoothing allowing pedestrians to follow a route with flexibility, similarly to real pedestrians.

E) Apply the proposed model to simulate a real urban environment. In this model pedestrians should interact with the environment in order to define their own activities, considering their individual profiles.

1.3 Delimitations

In general, the limitations of the model developed in this document are directly related to the level of sophistication required to represent Pedestrians activity. The model of pedestrian simulation proposed in this Doctoral Thesis was conceived for the representation of urban spaces. In these environments the complexity of the profile of each pedestrian is relevant and impacts simulation results, such as: Public transportation stations, shopping malls, indoor environments, etc. Agent complexity restricts, for reasons of computational performance, simulations of a large number of pedestrians, such as simulation of stadium evacuations or large structures. Moreover, the complexity of the human behavior poses many challenges to the modeling process, limiting the ability to reproduce behaviors and decisions of real pedestrians.

1.4 Background

Computational and technological developments allow the modeling of increasingly complex agents and to simulate environments more realistically, considering microscopic aspects, as individual preferences. Figure 2 shows the evolution of the representation of a pedestrian as a particle to a complex agent, and the relationship with relevant studies presented in the literature. In Figure 2, from bottom to top, agent modeling gains complexity as the agent's decision-making process incorporates skills and functions.

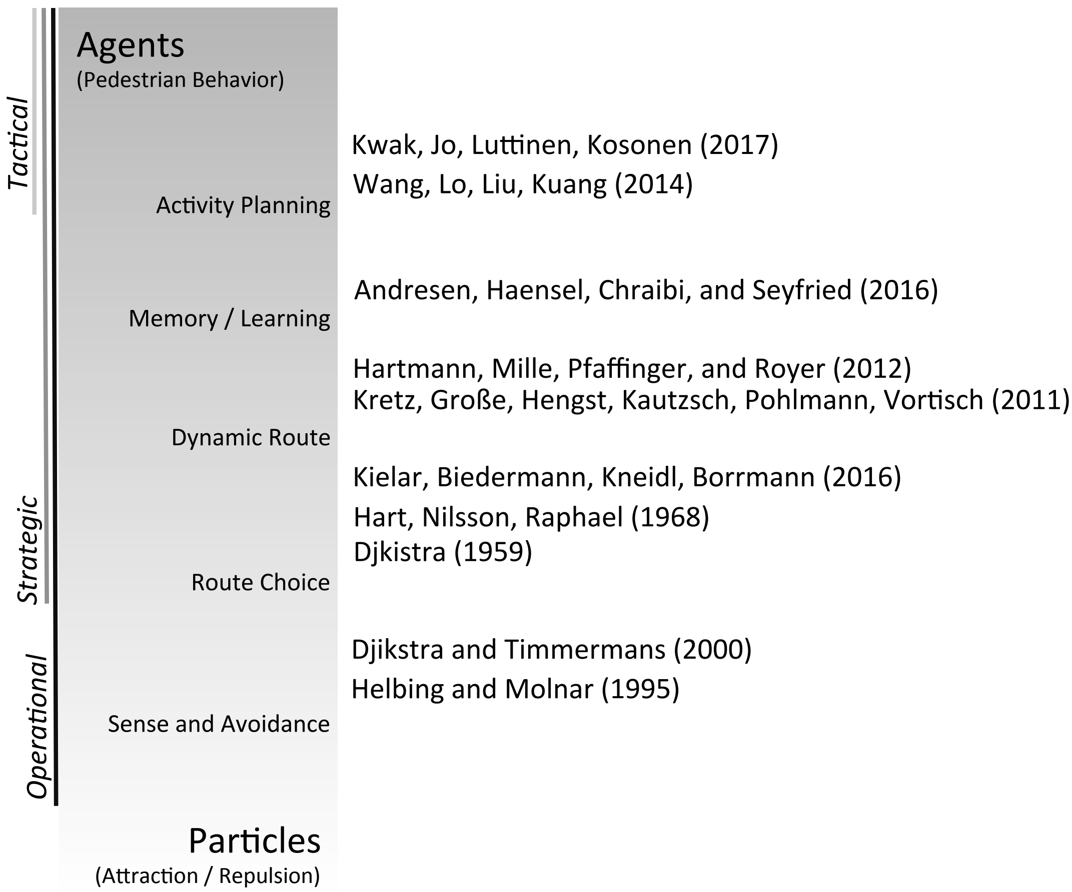


Figure 2 – Complex Pedestrian Agents Modeling

The first step to be modeled in the pedestrians' decision-making process is the sense and avoidance behavior. An agent should be able to perceive obstacles and other pedestrians in the environment and avoid them to follow its goal. The approaches to this problem fall, for the most part, into two major groups: Cellular Automata, as in Djikstra and Timmermans (2000) [2] and Newtonian Models, as in Helbing and Molnar (1995) [3].

Cellular automata based models consists of a regular grid of cells, where each cell has a finite number of states. The grid can be of any finite number of dimensions. The passage of time occurs discretely, and the state of a cell at time t is a function of the state of a finite number of cells called neighborhood at time t-1. Cellular automata is a widely used approach to demonstrate particle, pedestrian, and even automobile movement. Through simple rules, realistic macroscopic behaviors emerge. Several pedestrian simulation models described in the literature are based on Cellular Automata [4][5][6][7][8].

Newtonian forces based models are models where pedestrians are subjected to forces based on physical concepts described by Newton [9]. A classic implementation of this approach is the Social Forces Model (Helbing and Molnar, 1995) [3]. This implementation assumes that pedestrian movements can be described through vector forces derived from the pedestrians' internal motivations to perform certain actions. Through the concept of social forces, it is possible to represent many typical pedestrian behaviors, such as lane formation and oscillation of conflicting flows in bottlenecks.

According to Figure 2 the implementation of the strategic decision level of the pedestrian agent starts with the route choice. Given the initial position of an agent and its final destination, it must be able to identify a possible route to his goal. The route choice can consider several aspects. Traditionally, the route length is the most usual variable. The algorithm of Djikstra (1959) [10] guarantees to find the lower cost route between two nodes of a graph. The A* [11] algorithm adds to the Djikstra's algorithm the idea of heuristics, reducing its computational cost. Kielar et.al. (2016) [12] developed a model based on several route choice methods to identify all possible routes to be chosen by real pedestrians.

Besides choosing a route, pedestrians are able to constantly reevaluate and recalculate their routes based on observations of the environment. Kretz et. Al. (2011)

[6] proposes an evacuation model where pedestrians are able to identify the fastest route to their goal. The fastest route is dynamic, since it changes over time. In this model a navigation floor field covers the scenario and guides the pedestrians to the exits. The fastest route is found because pedestrians in the simulation environment cause disturbances in the floor field so that congested paths become less attractive. In a complementation of this approach Hartmann et al. (2012) [8] use more than one floor field in the same scenario. Pedestrians with equal destinations are grouped together and use the same floor field. Pedestrians of other groups cause a greater disturbance in the floor field, in this way, it is possible to represent the tendency of a pedestrian to avoid a conflicting flow of pedestrians.

The paper presented in Chapter 1 of this Doctoral Thesis describes a route choice model for pedestrians considering distances and interaction with other pedestrians. In the proposed model route choice process is internal to agent. The agent uses its perception of the environment and its beliefs to calculate the best route for himself. The agent desired direction of motion is not received information, like in floor field approaches. In this way, the individual profile of each agent impacts on the final result of the simulation. Pedestrians' grouping into groups with common goals, as in Hartmann et al. (2012) [8], is not a natural approach to simulate urban environments since pedestrians have distinct objectives, unlike evacuations. Model proposed in Chapter 1 represents the pedestrians' behavior to avoid conflicting flows. Furthermore, the model keeps typical pedestrians self-organization phenomenon, such as lane formation.

Many models of pedestrian simulation use floor field strategy to guide the agents [5][6][7][8]. In these models the scenario floor is discretized and each cell indicates the direction to be followed for a certain objective. The floor fields are constantly recalculated according to environmental variations. Chapter 4 of this Doctoral Thesis describes a mathematical method capable of providing an agent-orientation vector anywhere in the plane, resembling the implementation of a floor field. However, unlike a floor field, the vector field is continuous and does not belong to the scenario, but to the agent. The method proposed in Chapter 4 guides the pedestrian over a smoothed route by calculating orientation vectors.

Some simulation models limit the initial knowledge of the pedestrian about the geometric characteristics of the scenarios. The agent must combine learning activities and memorizing information. Andresen et al. (2016) [13] describe agents with capacity to assemble cognitive maps of the places where they were present, even without prior knowledge of the scenario. In Chapter 2 of this doctoral thesis it is presented a simulation model of pedestrians where the agents have limited knowledge about the state of the scenario, that is, the agents know the geometry of the spaces, however do not have complete information on the conditions of occupation. This limitation of agent knowledge has eliminated problems of over-organization of conflicting pedestrian flows, an emergent behavior of simulation not observed in real pedestrians.

Recent models give pedestrians strategic decision-making capabilities (Figure 2). At strategic level the pedestrian decides his departure time and his activities, that is, his place or places of destination. Kwak et al. (2017) [14] simulate the effect of congestion generated by pedestrians who decide to stop at an attractor in the environment during their travel. In the model the decision to stop at an attractor is influenced by other agents. Wang et al. (2014) [15] propose a model of attractiveness based on the visual field of the agent. This model is employed in simulation of shopping centers.

Chapter 5 of this document present a simulation model where agents can define partial destinations according to their profile. A pedestrian may decide to stop at places of their interest even without prior knowledge. The model allows the definition of complex agent profiles as well as complex profiles of stop locations. The greater the similarities between the profile of a pedestrian with the settings of a stopping place greater are the chances of a pedestrian deciding to stop at this location.

1.5 Document Structure

This document is organized in 7 chapters. The present chapter presents the contextualization of the work, the objectives and delimitations. Chapters 2 to 6 present a compilation of 5 articles, respecting the suggested model proposed by the post graduation program. Chapter 8 presents the conclusion and future developments.

Chapter 2 presents the paper "Pedestrian route choice model based on friction forces" [16]. (Werberich, B. R., Pretto, C. O., & Cybis, H. B. B. (2014). Pedestrian route choice model based on friction forces. *Simulation*, 0037549714547295.)

This paper describes the development of a route choice model based on friction forces. In Helbing and Johansson (2009) [17] the authors made the assumption that pedestrians avoid passing closer to other pedestrians with high relative velocity, minimizing the friction forces. The route cost calculation considers a balance between distance and the impedance generated by other pedestrians. Social Forces Model [3] describes the pedestrians walking behavior in the proposed model. SFM considers that pedestrians' motion can be described as a superposition of several forces. Regarding: Desired direction of motion ($\vec{e}$), forces exerted by the environment and by other pedestrians. The calculation of the impedance generated by other pedestrians' considers the difference of a pedestrian $\vec{e}$ vector and other pedestrians' velocities. Thus, a pedestrian avoid congestion and, mainly, a conflicting flow of pedestrians.

Simulations results shown that pedestrians choosing longer routes can have similar or better travel times. The ability of choosing not only the shorter route brings more realistic behaviors for the pedestrians' representation, especially with small differences in route lengths and higher congestion. Agents' profiles play an important role in the simulations. Pedestrians with higher desired speeds are more likely to choose longer routes to avoid congestion; higher speeds tend to generate higher impedances. This emergent behavior shown that pedestrians prepared to walk faster are also more willing to walk more to avoid congestion. Other emergent behavior shown lane formation into distinct routes, i.e., pedestrian with similar desired direction of motion grouped together in different routes in order to minimize friction forces between pedestrians.

Chapter 3 presents the paper "Pedestrians' route choice based on friction forces assuming partial and full environment knowledge" [18]. (Werberich, B. R., Pretto, C. O., & Cybis, H. (2014). Pedestrians' Route Choice Based On Friction Forces Assuming Partial And Full Environment Knowledge. *Transportation Research Board 93rd Annual Meeting* (No. 14-3067)).

This paper describes additional developments of the model presented on Chapter 2. As previously mentioned, the proposed model was capable to represent emergent behavior among interaction between agents. However, the lane formation into distinct routes sometimes converges to a super organization, not observed in the real world. Agents were capable to organize themselves in a way to completely avoid pedestrians traveling in the opposite direction. This organization is only possible when pedestrians have full knowledge of the network conditions, i.e., they know the velocity and position of all other pedestrians in the simulation.

In this paper, agents were modeled with partial knowledge of the network conditions. The knowledge was limited considering the pedestrian estimated field of view. In the real world it is not possible to know the network state before turning the corner.

Pedestrians with partial knowledge also presented unrealistic behavior. Some pedestrians got locked coming and going the same link multiple times. This strange behavior happened when pedestrians faced congestion on both sides of a link. The problem was that they don't remember the network condition of the links they had already traversed. For this reason, the second addition to the model was to provide agents with the ability to store previous information for traveled links. Pedestrians with partial knowledge of the network state and memory of the network state for the previously traversed links presented the more reasonable behavior under congested conditions.

Chapter 4 presents the paper "Calibration of a pedestrian route choice model with a basis in friction forces" [19]. (Werberich, B. R., Pretto, C. O., & Cybis, H. B. B. (2015). Calibration of a Pedestrian Route Choice Model with a Basis in Friction Forces. *Transportation Research Record: Journal of the Transportation Research Board*, (2519), 137-145.)

Simulation models have to be calibrated before being applied to real case studies. This paper shows the calibration process for the proposed route choice model. Calibrating a pedestrian route choice model is a complex task mainly for two reasons: (i) Many factors interfere on pedestrians' route choice; (ii) data collection is difficult. To overcome these difficulties real pedestrians were studied in a controlled environment. An experiment was set up inside the university campus. A scenario was built with 2-meter-high walls and two opposite entrances. A camera with top view recorded the interactions between pedestrians, inside the scenario.

Volunteers ware asked to walk inside the scenario. Some of them were instructed to walk in a predefined route, generating congestion. Other pedestrians, the objects of study, were instructed to freely walk. Data collection was a semi-automatic process for video analyses. Data were collected independently for each pedestrian in the experiment. Collected data made possible to validate and calibrate the model to represent the pedestrian tendency to avoid congestion. Simulation results indicate this model provides a promising approach for real case applications. Balance between impedance and distance could be easily calibrated with a single parameter.

Chapter 5 presents the paper: "*Following a route: a force field generated from a sequence of points on the plane*".

This paper presents a methodology to guide pedestrians in order to follow their determined routes. The model described in Chapter 2 defines the route of a pedestrian as a sequence of nodes in a graph. In a simplified way, the route is a sequence of points (x and y coordinates) in a plane. In a classical strategy the pedestrian has its desired direction of motion vector pointing to the first point of its route, when the pedestrian gets close to this point, his vector of desired direction of motion points to the next point, and so on.

The classic strategy used by a pedestrian to follow a sequence of points in a plane can generate unrealistic behavior, especially if exposed to interactions that may disturb the pedestrian path. The methodology presented in this paper defines a vector field from the sequence of points of a route. In this way, changes to the vector of desired direction of motion happen smoothly. The vector field provides the pedestrian orientation vector at any location in the simulation scenario. The strategy adopted gave the pedestrians smoother movements without sudden changes of direction and more natural movements returning to the route in case of deviations due to disturbances.

Chapter 6 presents the paper "Pedestrians' route choice model for shopping behavior" [20]. (Werberich, B. R., Pretto, C. O., & Cybis, H. B. B. (2016). Pedestrians' Route Choice Model for Shopping Behavior. *9th International Workshop on Agents in Traffic and Transportation.* (CEUR Vol-1678)).

After the calibration process, presented on Chapter 4, the model was able to simulate a real scenario. In this paper (Chapter 6) the model was applied to simulate a shopping mall environment. Simulate the pedestrians shopping behavior is particularly complex once route choice in shopping malls may be defined by a number of causal factors. Shoppers may follow a pre-defined schedule; they may be influenced by other people walking, or may want to get a glimpse of a familiar shopping. Proposed pedestrian model allows the representation of agents capable to perform both planned and unplanned behavior, depending on their profiles. Simulation results were compared to real data collected by video recording in a shopping mall.

The route cost calculation presented on Chapter 2 considers two factors: route length and the impedance generated by other pedestrians. For shopping behavior, a new factor is being considered in route cost calculation: attraction for areas of interest on the environment. A pedestrian may choose a longer and congested route to pass closer to an area of interest, even if not previously scheduled. The interest of an agent by a specific area on the scenario is highly related to their profile. The model allows the definition of properties representing the many different kinds and segments of stores. In a related way, pedestrians' profiles describe the probability of a pedestrian being attracted by each property.

Pedestrians not only pass closer to interest areas, they may stop in front a store for a while. Proposed model introduces the concept of hotspots. Hotspots are defined by a location in the environment and also for properties related to its characteristics. Once again, pedestrians' profile describes the probability of a pedestrian stop in a hotspot. Analysis from simulations indicates that the agents' behavior provides a promising approach for real case applications.

2. FIRST PAPER

“Pedestrian Route Choice Model Based on Friction Forces” [16]

Simulation

Simulation: Transactions of the Society for Modeling and Simulation International
1–11

DOI: 10.1177/0037549714547295
sim.sagepub.com
SAGE SCS

Pedestrian route choice model based on friction forces

Bruno Rocha Werberich, Carlos Oliva Pretto and Helena Beatriz Bettella Cybis

Abstract

This paper presents a pedestrian route choice model devised to represent the influence of the impedance generated by other pedestrians on the route choice process. This model is inspired by friction force equations, and considers that pedestrians avoid passing near other pedestrians with high relative velocity. The route choice process is based on a weighting of the impedance generated by pedestrians and the path length. A social force model was used to model pedestrian walking behavior. The model is able to reproduce emergent behavior among agents, allowing the assumption that the friction equations may provide a suitable approach to route choice behavior and can also be used as an indirect measure of pedestrian delay.

Keywords

Route choice, pedestrian simulation, modeling of pedestrians, pedestrian behavior

1. Introduction

The simulation of pedestrians in urban environments is a complex problem. In order to represent the motion of pedestrians more realistically, models are required to simulate several processes, including sense and avoidance of obstacles, interaction with other pedestrians, and route choice.

The simulation of a pedestrian's sense and avoidance of obstacles in most models reported in the literature can be regarded as using force-based approaches. In force-based models, agents evaluate forces exerted by the infrastructure and by other agents. Helbing and Molnár presented a relevant work on force-based models in which they use Newtonian mechanics and a continuous space representation to model a long-range interaction.[1] The social force model has been successful in reproducing various observed phenomena. The concept behind this approach suggests that the motion of a pedestrian can be described by the combination of several forces (including the repulsive forces from other pedestrians and walls) that result in the walking direction, at a certain desired speed.

Extending the traditional application of social force models, Helbing and Johansson proposed a social force model for simulating crowds.[2] In this model, the authors aggregate friction-inspired equations, based on pedestrians' relative speed, to the standard social force approach. The interactions with walls and other obstacles are treated analogously to pedestrians' interactions. The concept of friction between pedestrians adds an important component for the reasoning of pedestrian dynamics.

Collective behaviors frequently emerge from interactions among individuals. Under certain conditions, pedestrian flows form collective patterns of motion, such as shock waves in dense crowds, lanes of uniform walking directions in pedestrian counter flows, circulating flows at intersections, or oscillating flows at bottlenecks.[3] This is a crucial concept in the simulation of pedestrians.[4,5] This phenomenon, also called self-organization, is an emergent behavior that arises from the interactions between agents. Studies of self-organization in pedestrian crowds include pedestrian streams in corridors or alleys,[6–8] in addition to the movement of pedestrians through a waiting crowd.[7,9] More complex studies consider the escape of disoriented people from a room.[10]

Teknomo and Teknomo et al. described an approach based on route choice self-organization to model the dynamics of mobile agents,[11,12] such as pedestrians and

Universidade Federal do Rio Grande do Sul (UFRGS), Porto Alegre, Rio Grande do Sul, Brazil

Corresponding author:
Bruno Rocha Werberich, Av. Osvaldo Aranha, 99 - 5° andar, CEP 90.035-190, (LASTRAN), Porto Alegre, Rio Grande do Sul, Brazil.
Email: bruno.rwe@gmail.com

cars, on a simple network graph. This modeling approach is based on the route choice self-organization of multiple agents. The agents decide, when reaching a vertex, which edge to enter next. This decision is based on a set of rules that considers the agent's observation of the local environment. The model simulates only one-directional movement from the origin to the destination vertex.

In order to represent complex networks, such as urban scenarios, models need to include route choice capabilities. Pedestrians can use a wide range of algorithms to find the best route to reach a destination. The analysis of pedestrian route choice in urban areas may help understand the way pedestrians interact with each other. The route choice process can also include an element of collective behavior. Although the decision about what route a pedestrian will take during a trip is an individual decision, it is influenced by a wide range of factors, including the conditions of the environment and the presence of other pedestrians.

Compared to other modes of transport, modeling the pedestrian route choice process is complex because a pedestrian chooses a route from an infinite set of alternatives, weighing his comfort and safety needs with the delay cost.

Most walking processes, such as route selection strategies, are based on subconscious decisions. The perception of distance and directness are the most common reasons for choosing a particular route.[13] Pedestrians frequently choose the shortest route, although they are not aware of this utility maximization process.[14] Other factors that play an important role in route choice behavior are peoples' habits, number of crossings, pollution and noise levels, safety and shelter from poor weather conditions, and stimulations of the environment.[15] An understanding pedestrian behavior and how routes are chosen is essential for planning and designing public and private infrastructures.

Pedestrian models frequently assume a static route choice process. They are built on the assumption that pedestrians walk along the shortest path, defined before the trip starts, and that they try to walk through this path while avoiding collisions and other pedestrians. However, pedestrians frequently revise and alter their routes based on their instant evaluation of the general environment. Dynamic route choice models are, therefore, frequently required to represent real life conditions. They differ from their static counterparts in the sense that they represent route changes over time. They aim to provide a sounder representation of the route choice process, emulating the behavior of individual pedestrians while considering variations in the condition of the environment.

One interesting approach for pedestrian route choice is provided by Wagoum et al.[16] The model presents an event-driven way finding algorithm for evacuation scenarios. The algorithm operates on a graph-based structure. The modeled strategy consists of a combination of the shortest and quickest path. In contrast to the shortest path, the quickest path is dynamic and changes over time throughout the simulation timeframe. Pedestrians' decisions consider the observed environment, and the dynamic route choice is based on a cost-benefit analysis. The key element of Wagoum's approach is the estimation of travel times between the graph's nodes based on the observed velocity of other agents in the network.

Most relevant route choice models are concerned with pedestrians' evacuation. In the model proposed by Kretz et al.,[17] pedestrians adopt paths that present the minimal remaining travel time to the destination. Patil et al. presented an interactive algorithm to direct and control crowd simulations.[18] Their approach adopts user-specified guidance fields to direct the agents in a simulation performing a goal-directed navigation. The model developed by Treuille et al. unifies path planning and local collision avoidance by using a set of dynamic potential and velocity.[19] Banerjee et al. used layer intelligence from computer games to represent congestion avoidance.[20] The authors consider congestion of agents as a dynamic obstacle. Groups of unmoving pedestrians are considered as obstacles and agents tend to avoid them in their route choice.

Many models presented in the literature are concerned only with the quickest or shortest path.[21–23] The majority of these models assume that all pedestrians will choose routes by only considering such variables as distance and density of pedestrians. Sound route choice processes should also consider different pedestrian profiles, regarding characteristics such as their desired speed and direction. This paper presents a dynamic route choice model based on a combination of distance and impedance generated by other pedestrians. This model was devised to represent pedestrian route choice behavior in networks that resemble urban topology, with pedestrians having multiple origins and destinations.

The calculation of impedance is derived from the friction concept proposed by Helbing and Johansson.[2] The impedance generated by the friction equations involves variables related to the pedestrian's profile, such as the desired speed and other pedestrian velocities. The impedance can be used as an indirect measure of pedestrian delays.

2. The model

The aggregation of different levels of abstraction on a simulation model is a complex task. In most cases, each level of abstraction can be separately modeled on a multi-layer simulation approach.[24–26] The framework adopted to describe pedestrian motion in this model was divided in a three-layer structure responsible for: (i) representing the demand for travel; (ii) representing the simulation environment; and (iii) representing the movement of pedestrians and the process of the sense and avoidance of obstacles (Figure 1).

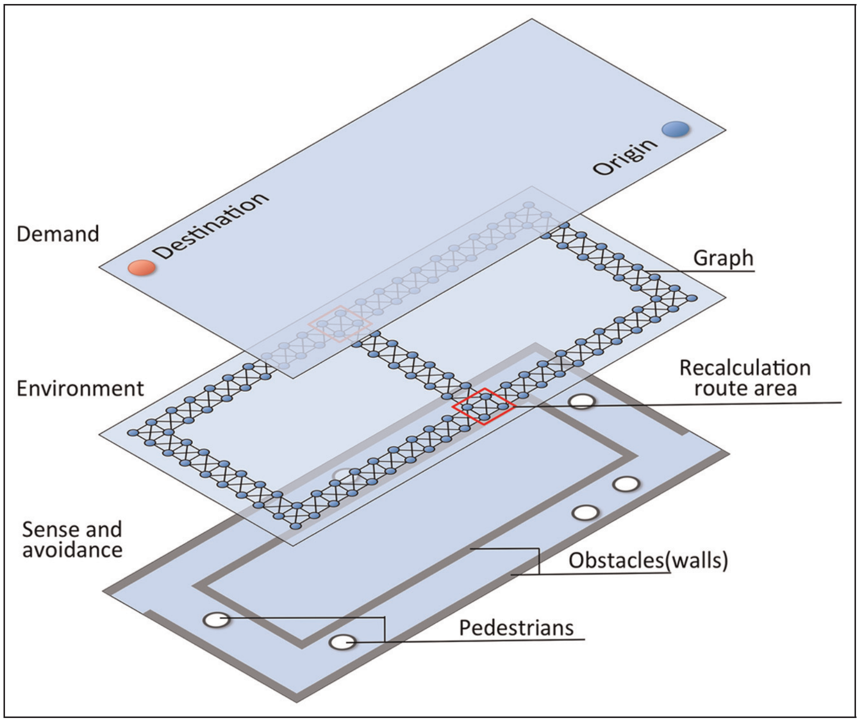


Figure 1. Multi-layer model.

2.1. Demand configuration

The demand for pedestrian trips is defined by a set of origin and destination pairs. Each origin–destination pair is associated to a number of total trips and a pedestrian generation rate. Origins and destinations are associated with the nearest nodes from the graph on the environment layer.

2.2. Environment configuration

The environment is described as a continuous space and is composed of geometric entities, such as rooms, doors, and other obstacles. The environment entities are linked by a graph-based structure. The graph provides a path to all entities. The graph generation process should guarantee that no edge of the graph intersects any walls or obstacles.

This layer also contains route recalculation areas where a pedestrian can choose between alternatives paths. The role of recalculation areas will be discussed later.

2.3. Pedestrian movement

The social force model describes pedestrian walking behavior in terms of the agents' low-level motion, collision avoidance, and velocity adaptation.[1] The social force model considers that pedestrian motion can be described as a superposition of several forces. Helbing and Molnár assume that these forces are a combination of psychological and physical forces.[1] Pedestrians freely walk on the modeling environment, seeking the next graph node of the designated route. Pedestrian movements are ruled by the sense and avoidance model and are not restricted to a strict set of links.

A pedestrian α who wants to reach his destination $\vec{r}_\alpha^0$ takes the shortest possible path. The pedestrian's trip will usually have some intermediate destinations, $\vec{r}_\alpha^1 \dots \vec{r}_\alpha^k$. Assuming that $\vec{r}_\alpha^k$ is the next partial destination, the desired direction of motion $\vec{e}_\alpha(t)$, according Helbing and Molnár,[1] will be:

$$\vec{e}_\alpha(t) = \frac{\vec{r}_\alpha^k - \vec{r}_\alpha(t)}{||\vec{r}_\alpha^k - \vec{r}_\alpha(t)||} \tag{1}$$

where $\vec{r}_\alpha(t)$ denotes the pedestrian's α position at time t.

Any pedestrian α presents a desired speed v_α^0 and a desired direction $\vec{e}_\alpha$. The desired velocity is, therefore, $\vec{v}_\alpha^0(t) = v_\alpha^0 \vec{e}_\alpha(t)$.

In case of deviations from the desired velocity, the pedestrian assume a current velocity $\vec{v}_\alpha(t)$. The pedestrian α tends to restore $\vec{v}_\alpha(t)$ within a certain relaxation time τ_α. Helbing and Molnár describe this adaptation by the acceleration term $\vec{F}_\alpha^0$:[1]

$$\vec{F}_\alpha^0(\vec{v}_\alpha, v_\alpha^0 \vec{e}_\alpha) = \frac{1}{\tau_\alpha}(v_\alpha^0 \vec{e}_\alpha - \vec{v}_\alpha) \tag{2}$$

Pedestrians feel uncomfortable close to other pedestrians and walls; therefore, the presence of pedestrian β will result in a repulsive force affecting the motion of pedestrian α. Helbing and Molnár represent this effect by $\vec{f}_{\alpha\beta}$:[1]

$$\vec{f}_{\alpha\beta}(\vec{r}^{\alpha\beta}) = -\nabla_{\vec{r}_{\alpha\beta}} V_{\alpha\beta}[b(\vec{r}_{\alpha\beta})] \quad (3)$$

where $V_{\alpha\beta}$ is the repulsive potential, represented by a monotonic decreasing function with equipotential elliptical lines. The elliptical shape reproduces the pedestrian's need for more space in the direction of motion; b is the semi-minor axis of the pedestrian ellipse defined by $\vec{r}_{\alpha\beta}$ ($\vec{r}_{\alpha\beta} = \vec{r}_\alpha - \vec{r}_\beta$). The resultant force exerted over a pedestrian is a superposition of three forces: the force to adapt the current velocity to the desired velocity ($\vec{F}^0_\alpha$), the forces exerted by other pedestrians ($\vec{f}_{\alpha\beta}$), and the forces exerted by walls and other obstacles.

3. Route choice process modeling

Route choice is a complex process to model because most route selection strategies are based on subconscious decisions. The perception of distance and directness are the most common reasons for choosing a particular route, however, other factors may also play an important role in this decision, such as safety, pavement conditions, density of people, and people walking in the opposite direction. This model assumes that the cost of a route is a function of two factors: the route length and the impedance generated by other pedestrians. The impedance generated by the friction between pedestrians is generated even before physical contact, representing the psychological tendency to avoid passing close to individuals with high relative velocity.[2] Pedestrians seek the route that minimizes a function of distance and the friction with other pedestrians.

The dynamic route choice process is represented by the flowchart in Figure 2. The pedestrian starts the route choice process as soon as he starts the trip. To choose the route, the pedestrian takes into account the distance between nodes and also the impedance generated by other pedestrians. Once a route is defined, the pedestrian travels on the route until he reaches a route recalculation area or the final destination.

The model requires a path finding algorithm to produce a traversable path between graph's nodes. The algorithm adopted to generate valid paths for any origin and destination in this implementation was the Dijikstra algorithm.[27] The calculation procedure starts at the destination node, covering all the possible paths to the origin node, assigning a cost for each link between the nodes. At the end of the process, the pedestrian chooses the path defined by nodes with the minimum accumulated cost. In most applications, cost is defined by the distance between nodes. In this formulation, cost is a combination of distance and a term that represents the impedance exerted by other pedestrians in the simulation. The impedance is calculated by the procedure described below.

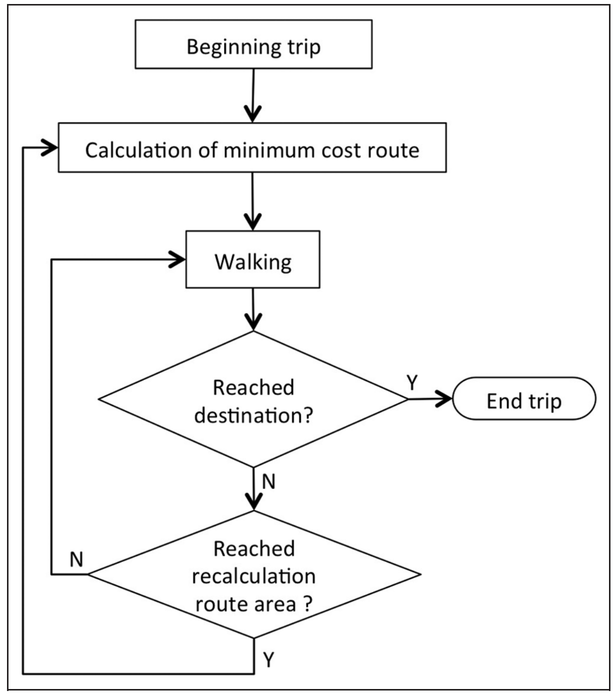


Figure 2. Dynamic route choice.

Figure 3 describes a pedestrian α who wants to find a route linking node O to node D. The algorithm traverses the graph assigning costs for each link between the nodes. Figure 3 shows, in the zoomed view, how the cost between nodes u and n is calculated for the pedestrian α. The impedance calculation process adopts a fictitious pedestrian α', positioned on node u, that has the same desired speed of pedestrian α ($\vec{v}^0_{\alpha'} = v^0_\alpha$) and a desired direction,$\vec{e}_{\alpha'}$, oriented to node n.

To estimate the impedance exerted over the pedestrian α', it is necessary to know the pedestrian desired velocity, $\vec{v}^0_{\alpha'}$ when he is trying to walk from $\vec{r}_u$ to $\vec{r}_n$:

$$\vec{v}^0_{\alpha'} = \frac{\vec{r}_n - \vec{r}_u}{||\vec{r}_n - \vec{r}_u||}.v^0_\alpha \quad (4)$$

The calculation of the impedance exerted by other pedestrians over α' requires the definition of neighborhood areas. A radius R_n, around the graph nodes, limits these areas. The impedance is evaluated by the difference between $\vec{v}^0_{\alpha'}$ and the current velocity of other pedestrians $\beta(\vec{v}_\beta)$, walking in the neighborhood area. Only pedestrians within the neighborhood area of node n are considered in the impedance estimation.

The impedance perceived by the fictitious pedestrian α' to walk from node u to $n(I_\alpha)$ is:

$$I_{\alpha'} = \sum_\beta ||\vec{v}_\beta - \vec{v}^0_{\alpha'}|| \quad (5)$$

The value of $I_{\alpha'}$ is normalized over a settable parameter $I_{\max}$. The cost perceived by the pedestrian α to walk from

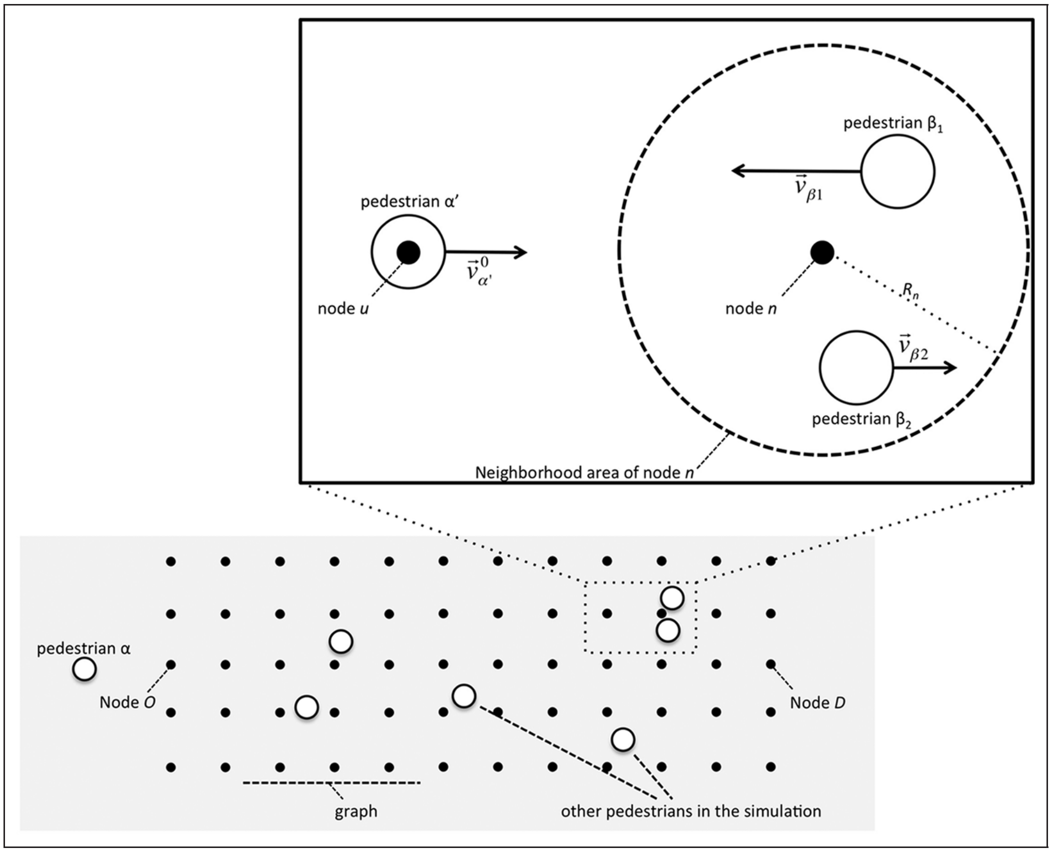


Figure 3. The route choice model.

node u to n, $W_{\alpha}^{u,n}$, is a balance between distance and the impedance exerted by other pedestrians:

$$W_{\alpha}^{u,\,n} = ||\vec{r}_n - \vec{r}_u|| \cdot (1 + I_{\alpha'}/I_{max}) \tag{6}$$

The described procedure is repeated until all possible paths costs are defined. Pedestrian α chooses the route with the lowest cost. The algorithm adopted to calculate the motion cost for pedestrian α' from node u to n is presented below (Algorithm 1).

One important aspect of the model configuration is the radius of the neighborhood areas (R_n) and the granularity of the nodes on the graph. The radius should ideally cover the maximum distance between nodes without overlapping, to reduce the probability of over counting or missing pedestrians. Regarding the granularity of the graph nodes, some issues should be considered when defining the modeling environment. Each node provides an impedance measure in its neighborhood area. If the distance between nodes is too large, and consequently the neighborhood area is too big, the estimation of the impedance could not capture the real pedestrians' organization. On the other hand, if a graph is too dense, the performance of the model can be jeopardized due to computation costs.

```
Double Cost_from_node_u_to_n(Node u, Node n, Pedestrian A)
{
 Double Absolute_Impedance = 0;
 Vector vA = Normalize(n.position - u.position) * A.DesiredVelocity;
 Q = List with all Pedestrians in the simulation;

 foreach Pedestrian B in Q
        if(DistanceBetween(B, n) < n.NeighborhoodRadius)
               Absolute_Impedance += Module(B.currentVelocity - vA);
        end if;
 endforeach;

 return Module(n.position - u.position) * (1 + Absolute_Impedance/ Max_Impedance);
}
```

Algorithm 1.

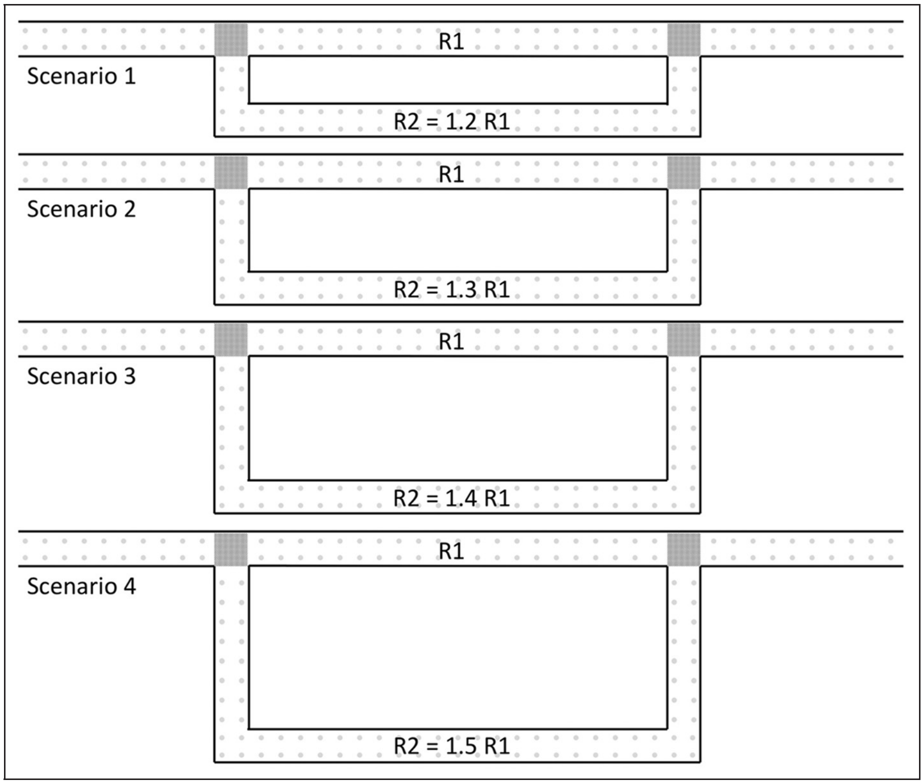


Figure 4. The four different scenarios.

I_{max} in equation (6) is a key parameter in the calculation of the cost perceived by pedestrians (W). This parameter acts as weighting factor between travel distance and the perceived impedance. The higher the value of I_{max}, the lower the willingness of pedestrians to choose an alternative longer route. The I_{max} is a calibration parameter that should be adjusted to reflect the willingness of pedestrians to trade for longer routes, depending on the pedestrian density on the shortest route. The I_{max} is also an individual pedestrian parameter that allows representation of multiple profiles.

4. Simulations

This section presents the results of simulations derived from the implementation of the model. The main goals of these simulations were to provide a realistic representation to evaluate the emergent behavior of pedestrians, their overall behavior, and to perform a conceptual validation of the model.

The experiment developed to accomplish the simulation objectives involved the combination of two controllable parameters, the scenario layout and the pedestrian generation rate:

- Scenario layout (S) – four levels:
  S1 = Scenario 1; S2 = Scenario 2; S3 = Scenario 3; S4 = Scenario 4
- Pedestrian generation rate (F) – three levels (pedestrians/s):
  F1 = 2.4; F2 = 4.0; F3 = 5.6

Figure 4 illustrates the four different scenarios, composed of two alternative routes, indicating the shortest route, R1, and the length of the alternative route, R2, for each scenario. The number of pedestrians who depart from left to right is equal to the number of pedestrians who travel in the opposite direction. The conflicting flows generate congestion in the network. The hatched zones are the route recalculation areas. The pedestrian route choice is always re-evaluated when reaching these areas.

The social force model parameters were configured as in Helbing and Molnár.[1] The I_{max} value was 3.9. The average desired velocity of pedestrians was 1.1 m/s with a standard deviation of 0.2 m/s.

The simulation results led to a qualitative and a quantitative analysis. The qualitative analysis is concerned with the pedestrian behavior that emerges from the route choice model. The quantitative analysis regards the numerical

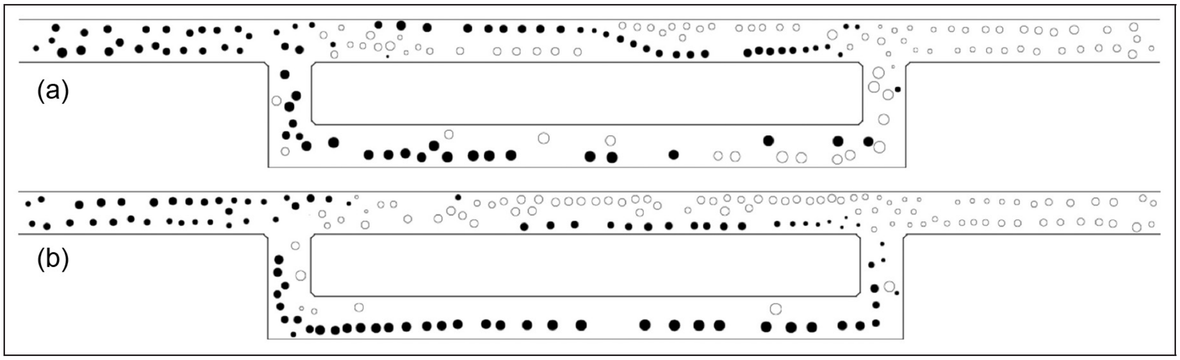


Figure 5. Simulation views.

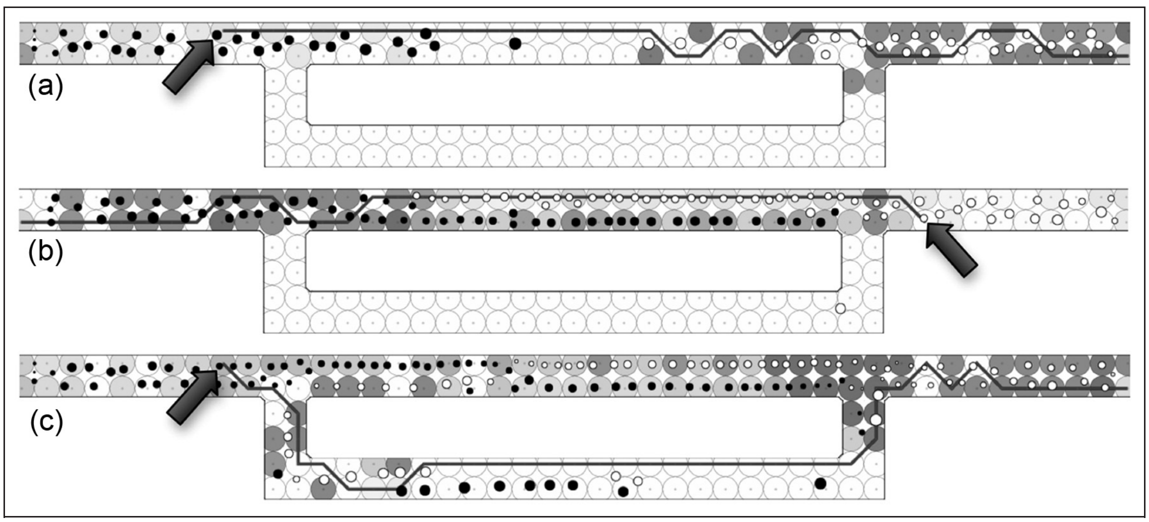


Figure 6. Impedance map.

results of the simulations, for the combination of network layouts and pedestrian densities.

4.1. Qualitative analysis

A detailed qualitative analysis from the simulation images demonstrated that the model provides sound representations for pedestrian behavior.

Figure 5(a) shows an instant of the simulation. Full circles symbolize pedestrians traveling from left to right and empty circles symbolize pedestrians traveling in the opposite direction. The diameter of the circle is a measure of the pedestrian's current speed. It is clear that route R1 is more congested than R2 and has lower speeds.

During the simulation, the lane formation of pedestrians moving in the same direction may occur in distinct routes. Lane formation happens because one pedestrian perceives the concordant flow of pedestrians with lower impedance than the opposing flow. Figure 5(b) shows one instant in the simulation when route R1 is predominantly occupied by empty circles and route R2 predominantly occupied by full circles.

The pedestrians' reasoning about the choice of route can be verified in Figure 6, which illustrates the impedance perceived by pedestrians. The impedance value was associated with a color scale. The color scale varies from light gray (for lower impedance) to dark gray (for higher impedance). Figure 6(a) shows the perceived impedance of the pedestrian indicated by the arrow at the route choice instant; the indicated path line is the chosen route. The gray circles are neighborhood node areas. In Figure 6(b), the pedestrian indicated by the arrow perceives the lane formation as a facilitator of the trip, choosing his route following the lane. Figure 6(c) shows the moment when the pedestrian chooses the longer route, when the shorter route becomes too congested.

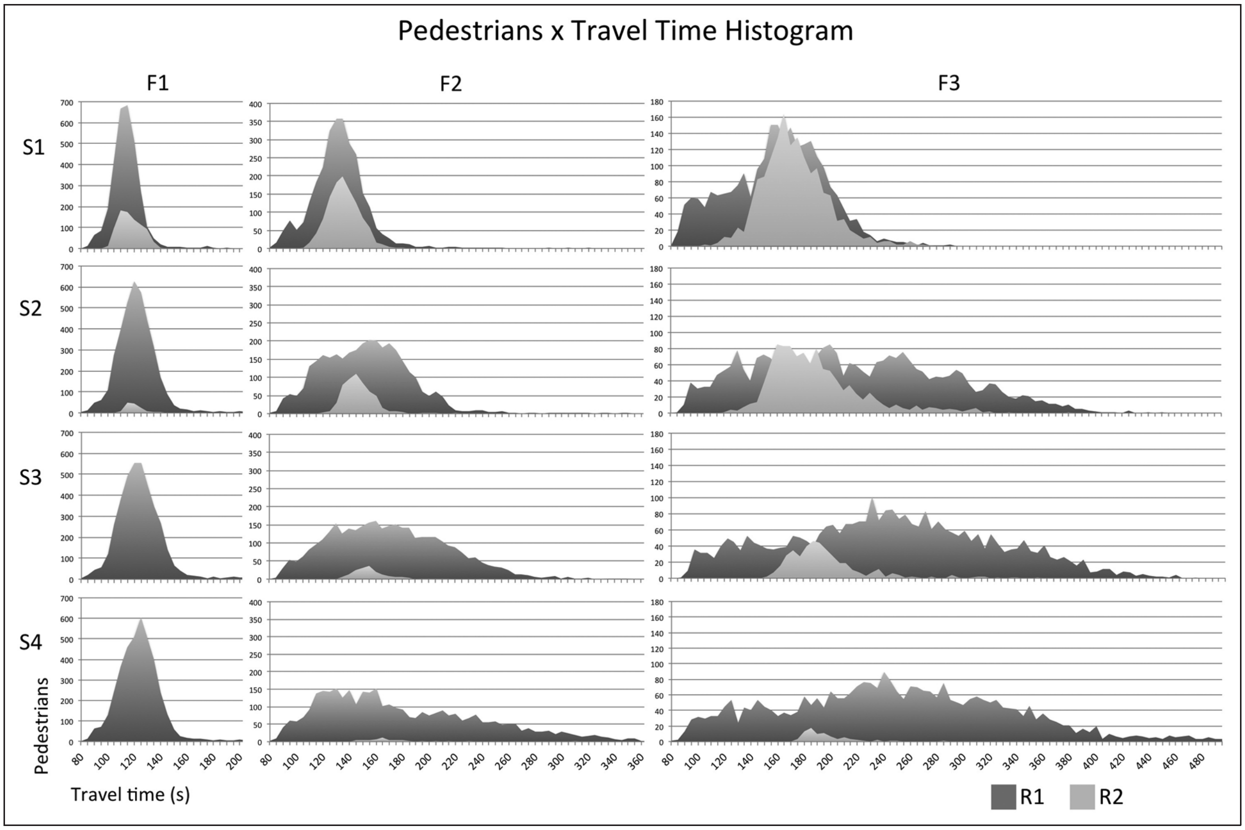


Figure 7. Travel time histogram.

4.2. Quantitative analysis

This analysis was developed to assess the ability of the model to represent expected pedestrian behavior.

Figure 7 presents 12 histogram charts of simulated travel times. Each histogram shows the pedestrians' travel time distribution for the combination of the controllable parameters described above: Scenarios (S1, S2, S3, S4) and pedestrians generation rates (F1, F2, F3). Each histogram chart is the result of 10 simulation runs totaling 3500 pedestrians.

For the model conceptual validation some expected results should be observed:

(i) Higher pedestrian generation rates produce congestion, increasing the overall travel times and the proportion of pedestrians opting for the longer route in order to avoid congestion.
(ii) The relationship between the lengths of the shorter and the longer route affects the percentage of pedestrians choosing the longer route. The longer the route, the less attractive it is.
(iii) Pedestrians who choose longer routes to avoid congestions are not expected to experience significant travel time penalties.

Regarding the expected result (i), it is noticeable in Figure 7 that higher generation rates of pedestrians lead to higher numbers of pedestrians in the alternative route. Pedestrians only prefer to travel on a longer route if they estimate that the impedance imposed by other pedestrians will affect their travel times.

The travel time distributions of pedestrians on both routes (Figure 7) indicate that the pedestrians' willingness to change to a longer route decreases as the length of the alternative route increases. Pedestrians were discouraged from choosing extremely longer routes. The willingness of a pedestrian to choose a longer route can be set trough the $I_{\max}$ parameter. However, the behaviors related to the expected results (i) and (ii) remain valid. Figure 8 shows the percentage for the total population of pedestrians in each simulation that chose the longer route, R2.

Combining scenarios with longer alternative routes and higher pedestrian generation rates produces a big congestion. In these situations, the distributions show pedestrians with extremely long travel times. This effect is probably due to factors related to the social force model itself. In some situations the pedestrians' density reached the boundaries of practical use of the model, and imposes a different approach regarding social force model implementation. Helbing and Johansson propose an adaptation of the social

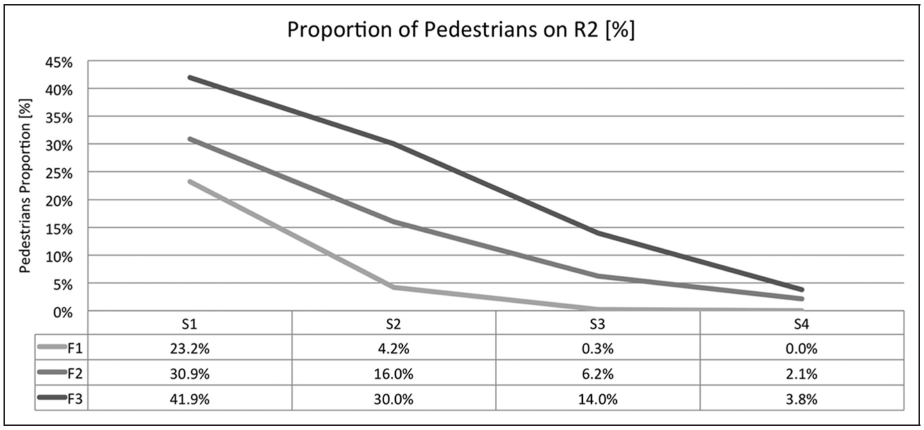


Figure 8. Proportion of pedestrians on R2

Table 1. Average travel time (s).

	S1				S2				S3				S4			
	R1		R2		R1		R2		R1		R2		R1		R2	
	avg	sd	avg	sd	avg	sd	avg	sd	avg	sd	avg	sd	avg	sd	avg	sd
F1	117	13	119	9	126	22	123	6	128	25	131	7	129	25	-	
F2	135	21	138	12	155	34	151	14	173	43	157	14	185	64	176	16
F3	162	36	175	24	221	72	190	35	245	79	197	32	252	87	196	15

Table 2. Travel time gain (R2).

	S1	S2	S3	S4
F1	2.9%	7.4%	5.6%	-
F2	4.8%	15.7%	26.5%	36.5%
F3	5.4%	29.2%	32.3%	37.0%

force model to better represent situations of high density of people.[2]

Table 1 shows the average travel time and travel time standard deviation for each route and simulation. The standard deviation increases as congestion and travel times increase. The expected results (i) and (ii) could again be observed. Increasing the frequency of pedestrian generation in the simulation also increases the average travel time. Similarly, the higher the length of R2, the higher is the average travel time. The proportion of pedestrians on R2 decreases when the length of R2 increases, leading to longer travel times in R1.

The average travel time of pedestrians on route R2 is, in most cases, lower than the time of pedestrians who chose

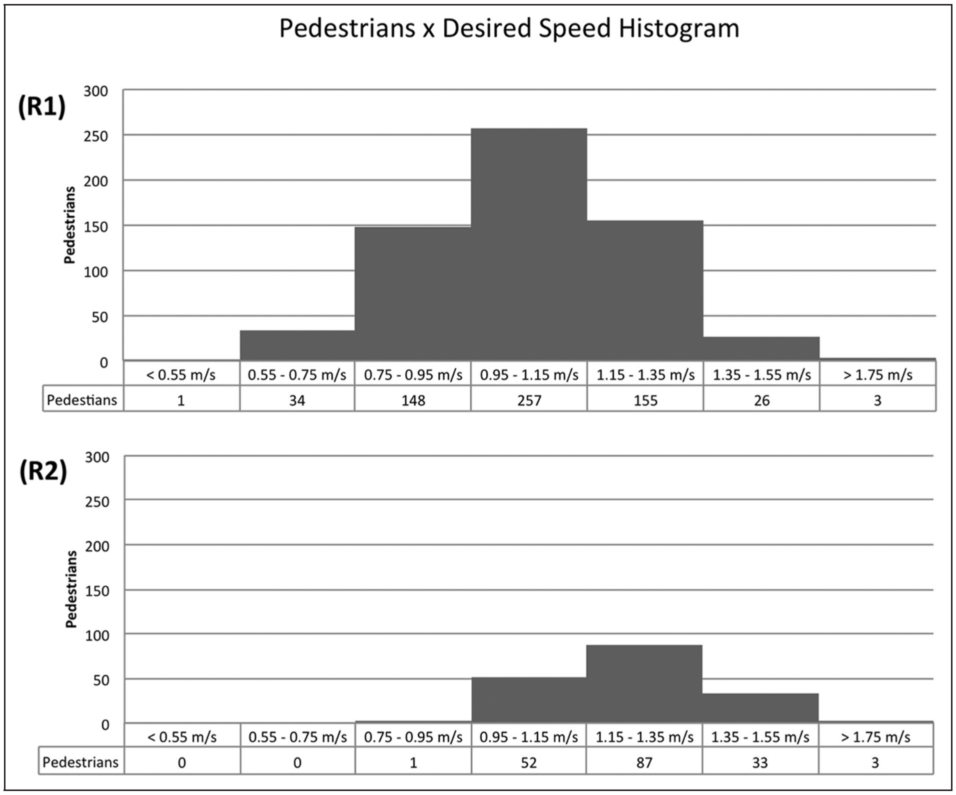


Figure 9. Desired speed histogram at R1 and R2.

the shorter route R1 (Table 1). However, a more detailed analysis was performed to further explain the expected behavior (iii).

As congestion conditions varies along the simulated period, it is important to evaluate the travel times difference experienced by pedestrians that chose alternative routes R1 and R2 at similar conditions. To eliminate undesirable discrepancies in the analysis, the simulation time was divided into 10 s intervals, grouping pedestrians who started their travel within the same time interval. Pedestrian groups in which all members chose the same route were not considered in this analysis. Table 2 shows the average gain in travel time of pedestrians who chose R2 in comparison to those who chose R1 for each interval.

The increasing volume of pedestrians has a direct relationship with the time saved by pedestrians who choose R2. The more congested the simulation environment, the higher the travel time gain of pedestrians who chose the longest route.

To explore the applicability of the model formulation, one of the main objectives of the simulations performed was to understand the underlying relationships that emerged from the model. Was there any relationship between pedestrians profiles, i.e. pedestrians' desired speed and their choice of route? For this analysis, a simulation with 800 pedestrians was performed for scenario S2 and generation frequency F2. The desired speeds of pedestrians on both routes can be analyzed in Figure 9.

Pedestrians with higher desired speed are more likely to choose the longer route, R2, than a slower pedestrian. This effect is observed because for the calculation of friction with other pedestrians, higher speeds tend to generate higher impedance. Thus, pedestrians prepared to walk faster are also more willing to walk farther, thus diverting from the congested area.

5. Conclusions

The modeling approach presented in this paper provides a sound representation of pedestrian route choice dynamics. Route choice is based on a combination of distance and the impedance generated by other pedestrians. The model adopts a pedestrian friction concept to calculate impedance. The analysis from simulations indicates that the emerging behavior of this model provides a promising approach for real case applications.

Interesting pedestrian route choice behaviors emerged from the model. Pedestrians on longer routes presented travel times similar to those of pedestrians traveling shorter routes. Pedestrians who choose the longest route tended to have a higher desired speed. Pedestrian dynamics presented a sound lane formation behavior. The lane formation of concurrent flows occurred at the same route or was segregated into distinct routes.

The emergent behavior from the model allows the assumption that the friction equations adopted in this modeling may provide a suitable approach to route choice behavior and can also be used as an indirect measure of pedestrian delay.

A video showing the simulation scenario S1 with pedestrian generation rate F3 is available on YouTube under http://youtu.be/m380wXUVp2Q.

Funding

This work was supported by the National Council for the Improvement of Higher Education (CAPES) and National Council for Scientific and Technological Development (CNPq), both of Brazil.

References

1. Helbing D and Molnar P. Social force model for pedestrian dynamics. *Phys Rev E Stat Phys Plasmas Fluids Relat Interdisciplin Top* 1995; 51: 42–82.
2. Helbing D and Johansson A. *Pedestrian, crowd and evacuation dynamics*. Swiss Federal Institute of Technology, 2009.
3. Helbing D, Buzna L, Johansson A, et al. Self-organized pedestrian crowd dynamics. *Transp Sci* 2005; 39 (1): 1–24.
4. Helbing D, Farkas I and Vicsek T. Simulating dynamical features of escape panic. *Nature* 2000; 407: 487–490.
5. Sumpter D. The principles of collective animal behaviour. *Phil Trans R Soc London Ser B* 2006; 3615–22.
6. Helbing D. A mathematical model for the behavior of pedestrians. *Behav Sci*. 1991; 36: 298–310.
7. Helbing D. *Verkehrsdynamik* [Traffic dynamics]. Berlin: Springer, 1997.
8. Helbing D, Molnár P, Farkas I, et al. Self-organizing pedestrian movement. *Environ Plann B* 2001: 28: 361–383.
9. Helbing D and Molnár P. Self-organization phenomena in pedestrian crowds. In: Schweitzer F (ed) *Self-organization of complex structures: from individual to collective dynamics*. London: Gordon and Breach, 1997, pp.569–577.
10. Isobe M, Helbing D and Nagatani T. Many-particle simulation of the evacuation process from a room without visibility. *Phys Rev E Stat Nonlinear Soft Matter Phys* 2004; 69: 066132.
11. Teknomo K. 2008. Modeling mobile traffic agents on network simulation. In: *Proceedings of the 16th annual conference of the Transportation Science Society of the Philippines (TSSP)*, Manila, 2008.
12. Teknomo K, Bauer D and Matyus T. Pedestrian route choice self-organization. In: *Proceedings of the 3rd international symposium of simulation in transportation*, Gold Coast, Australia, 2008.
13. Hill MR. *Spatial structure and decision-making of pedestrian route selection through an urban environment*. PhD Thesis, University Microfilms International, 1982.
14. Senevarante PN and Morall J. Analysis of factors affecting the choice of route of pedestrians. *Transp Plann Technol* 1986; 10: 147–159.
15. Papadimitriou E. Theory and models of pedestrian crossing behaviour along urban trips. *Transp Res Part F Traffic Psychol Behav* 2012; 15: 75–94.
16. Wagoum AUK, Seyfried A and Holl S. Modeling the dynamic route choice of pedestrians to assess the criticality of building evacuation. *Adv Complex Syst* 2012; 15(7). doi: 10.1142/S0219525912500294.
17. Kretz T, Große A, Hengst S, et al. Quickest paths in simulations of pedestrians. *Adv Complex Syst* 2011; 14: 733–759.
18. Patil S, Van Den Berg J, Curtis S, Lin MC and Manocha D. Directing crowd simulations using navigation fields, *IEEE Trans Visualization Comput Graphics* 2010; 17(2): 244–254.
19. Treuille A, Cooper S and Popović Z. Continuum crowds. *ACM Trans Graphics* 2006; 25(3):1160–1168.
20. Banerjee B, Abukmail A and Landon K. Layered intelligence for agent-based crowd simulation. *Simulation* 2009; 85: 621–633.
21. Kirik ES, Yurgel'yan TB and Krouglov DV. The shortest time and/or the shortest path strategies in a CA FF pedestrian dynamics model. *J Siberian Fed Univ Math Phys* 2009; 2: 271–278.
22. Dressler D, Groß M, Kappmeier J, et al. On the use of network flow techniques for assigning evacuees to exits. *Procedia Eng* 2010; 3: 205–215.
23. Lämmel G and Plaue M. Getting out of the way: collision avoiding pedestrian models compared to the real world. In: Weidmann U, Kirsch U and Schreckenberg M (eds) *Pedestrian and evacuation dynamics 2012*. Berlin: Springer, 2014.
24. Gaud N, Galland S, Gechter F, et al. Holonic multilevel simulation of complex systems: application to real-time pedestrians simulation in virtual urban environment. *Simul Model Pract Theory* 2008; 16: 1659–1676.
25. Hoogendoorn S, Bovy P and Daamen W. Microscopic pedestrian wayfinding and dynamics modelling. In: Schreckenberg M and Sharma S (eds) *Pedestrian and evacuation dynamics*. Berlin: Springer, 2002, pp.123–155.
26. Pretto CO, Jacobsen AC and Cybis HBB. A multi-layer simulation model for vehicle and pedestrian. In: *Proceedings of the 90th Annual Meeting of the Transportation Research Board*, Vol. 1, Washington, 2011, pp.1–15.
27. Dijkstra E. A note on two problems in connection with graphs. *Numer Math* 1959; 1: 269–271.

Author biographies

Bruno Werberich is a doctoral student at the Federal University of Rio Grande do Sul, in the Department of Transportation and Production Engineering, Porto Alegre, Brazil.

Carlos Pretto is a professor at the Federal University of Pelotas (UFPEL), Center for Mercosul Integration, Eldorado do Sul, Brazil, and also a guest researcher at the Federal University of Rio Grande do Sul, Porto Alegre, Brazil. Research topics include pedestrian simulation, software development, and power systems.

Helena Beatriz Bettella Cybis is a full professor at the Federal University of Rio Grande do Sul, Transport Systems Laboratory (LASTRAN) in the Department of Transportation and Production Engineering, Porto Alegre, Brazil.

3. SECOND PAPER

“Pedestrians’ Route Choice Based on Friction Forces Assuming Partial and Full Environment Knowledge” [18]

PEDESTRIANS' ROUTE CHOICE BASED ON FRICTION FORCES ASSUMING PARTIAL AND FULL ENVIRONMENT KNOWLEDGE

Bruno Rocha Werberich, Mr.

Research, Department of Production Engineer, Federal University of Rio Grande do Sul, Porto Alegre, Brazil. Tel +55 (51) 33083596, Fax +55 (51) 33084007, Av Osvaldo Aranha 99, 5 andar. E-mail: bruno.rwe@gmail.com.

Carlos Oliva Pretto, Dr.

Research, Department of Production Engineer, Federal University of Rio Grande do Sul, Porto Alegre, Brazil. Tel +55 (51) 33083596, Fax +55 (51) 33084007, Av Osvaldo Aranha 99, 5 andar. E-mail: cpretto@gmail.com.

Helena Cybis, PhD.

Associate Professor, Department of Production Engineer, Federal University of Rio Grande do Sul, Porto Alegre, Brazil. Tel +55 (51) 33083596, Fax +55 (51) 33084007, Av Osvaldo Aranha 99, 5 andar. E-mail: helenabc@producao.ufrgs.br.

Word count:	4.242 (7500 maximum)
Tables and figures:	1,750 (7*250 words each table or figure)
Total words:	5992

ABSTRACT

This paper presents a pedestrian route choice model. The model explicitly represents the interaction between pedestrians as an impedance force that influences pedestrians route choice. This model approach is inspired by friction forces equations, considering that pedestrians avoid passing near other pedestrians with high relative velocity. The route choice process is a function of the impedance force and path length. The social force model was used to model pedestrians walking behavior. A key element in this paper is the level of knowledge that pedestrians have about the network condition. The model reproduces three different levels of pedestrians' knowledge: (i) pedestrians with full knowledge about the network, (ii) pedestrians with partial knowledge and (iii) pedestrians with partial knowledge and a memory of past experiences. This article presents the resulting routes and travel times and discusses the differences and advantages of each level of pedestrians' knowledge implementation.

1. INTRODUCTION

Realistic representations of pedestrians' motion require the simulation of several processes, including path planning, sense and avoidance of obstacles, interaction with other pedestrians and route choice.

Most microscopic models that simulate pedestrians' sense and avoidance of obstacles reported in the literature can be classified as force-based approaches. In force-based models, agents evaluate forces exerted by the infrastructure and by other agents. Helbing and Molnár (1) present a relevant work about force-based model, in which the authors use Newtonian mechanics in a continuous space representation to model a long-range interaction. The social force model has been successful in reproducing various observed phenomena. This model approach considers that the motion of a pedestrian can be described by the combination of several forces (including repulsive forces from other pedestrians, walls etc.) that results in the pedestrian's direction at a certain desired speed.

Extending the traditional application of Social Force models, Helbing and Johansson (2) propose a Social Force Model for simulating crowds. In this model, the authors aggregate friction-inspired equations, based on pedestrians' relative speed, to the standard Social Force approach. The concept of friction between pedestrians adds an important component for the reasoning of pedestrians' dynamics.

The idea that collective behavior emerges from interactions among individuals is a crucial concept to study simulation of pedestrians (3)(4). Examples of such collective behaviors are the lane formation, and the oscillation of the passing direction at bottlenecks (5)(1).

The route choice process can also include an element of collective behavior. Although pedestrians' route choice is usually an individual decision, it is influenced by a wide range of factors, including the conditions of the environment and the presence of other pedestrians. Compared to other trip modes, modeling the pedestrian route choice is a complex process, since a pedestrian chooses a route from an infinite set of alternatives, weighing his comfort, safety needs and delay costs.

The majority of pedestrians' models can be classified into two categories: (i) models where pedestrians/agents don't have imbedded route choice algorithms (the route choice process can or cannot emerges from the simulation) and; (ii) models where agents have imbedded route choice algorithms (6).

The selection of alternative routes in the first category happens as self-organization phenomena. This phenomenon is an emergent behavior that arises from the interaction between agents. These models are not suitable for wide-open spaces and complex urban networks.

Models from the second category present explicit route choice capabilities. Pedestrians adopt some sort of function to find routes to the destination. These models can present static or dynamic route choice process. Static route choice models are built on the assumption that pedestrians walk along the shortest path, defined before the trip starts, and try to walk through this path while avoiding collisions. Dynamic route choice models differ from their static counterparts on the sense they represent route changes over time. They aim to provide a sounder representation of the route choice process, emulating the behavior of individual pedestrians while considering variations in the environment.

Several walking processes, such as route selection strategies, are based on subconscious decisions. The perception of distance and directness are the most common reasons for choosing a particular route (7). Pedestrians frequently choose the shortest route, although they are not aware of this utility maximization process (8). Most models presented in the literature are concerned only with the quickest or shortest path, like Kirik et. al. (9), Dressler et. al. (10) and Lämmel et. al. (11). However, other factors play an important role in route choice behavior, such as, peoples' habits, number of crossings, pollution and noise levels, safety and shelter from poor weather conditions, and stimulations of the environment (12). Understanding pedestrians´ behavior and how routes are chosen is essential for planning and designing public and private infrastructures.

Most relevant route choice models are concerned with pedestrians' evacuation. In Kretz et. al. (13), for example, pedestrians paths are chosen based on the minimal remaining travel time to the destination. Patil et. al. (14) propose an interactive algorithm to direct and control crowd simulations. Their approach adopts user-specified guidance fields to direct the agents in a simulation, performing a goal-directed navigation. The model by Treuille et. al. (15) unifies path planning and local collision avoidance by using a set of dynamic potential and velocity.

One interesting approach for pedestrian route choice is provided by Wagoum et. al. (16). The model presents an event-driven way finding algorithm for evacuation scenarios. The algorithm operates on a graph-based structure. The modeled strategy consists on a combination of shortest and quickest path. In contrast to the shortest path, the quickest path is dynamic and changes over time throughout the simulation timeframe. Pedestrians´ decisions consider the observed environment, and the dynamic route choice is based on a cost-benefit analysis. The key element of Wagoum's approach is the estimation of travel times between the graph´s nodes based on the observed velocity of other agents in the network.

Generally, pedestrians choose routes in order to reach their goals with less effort, in a safe and comfortable trip. In most cases, pedestrians have a good knowledge about their route options and are also able to estimate the number of pedestrians on each route. In both modeling strategies (dynamic and static), they assume that the pedestrian has full knowledge of the route conditions at the decision time. Sometimes, this assumption can lead to unrealistic simulations results.

This paper presents a dynamic route choice model based on a combination of distance and the impedance generated by other pedestrians. The calculation of the impedance is derived from the friction concept proposed by Helbing and Johansson (2). The impedance generated by the friction equations involves variables related to the pedestrian's profile, like the desired speed and other pedestrians' velocity. The route choice model presented in this paper considers three different levels of pedestrians' knowledge about the environment: pedestrians with full knowledge about the network state; pedestrians with partial knowledge; and pedestrians with partial knowledge and a memory about past experiences. The simulations' analysis allowed understanding the advantages and differences between the three implementations.

2. THE MODEL

The aggregation of different levels of abstraction on a simulation model is a complex task. In most cases, each level of abstraction can be separately modeled on a multi-level simulation approach (17).

2.1. Model Framework

The framework adopted to describe pedestrian motion in this model was divided in a three-layer structure responsible for: (i) representing the demand for travel, (ii) representing the simulation environment, and (iii) modeling the movement of pedestrians and the process of the sense and avoidance of obstacles, considering pedestrians with three different level of traffic conditions knowledge: full knowledge, partial knowledge and partial knowledge with memory.

- Configuration of the modeling demand: The demand for pedestrian trips is defined by a set of origin and destination pairs. Each origin-destination pair is associated to a number of pedestrian trips and a pedestrian generation rate. Origins and destinations are nodes from the graph layer.
- Configuration of the modeling environment: The environment is composed by geometric entities such as rooms, doors, and others, and is described as a continuous space. The environment and its entities are linked by a graph-based structure. The graph generation process should provide a valid path to all entities and guarantee that no edge of the graph intersects any wall or other obstacles in the environment.
- Pedestrian motion: sense and avoidance modeling: The Social Force model (1) describes the pedestrian walking behavior, regarding the agents' low level motion - collision avoidance and velocity adaptation. The social force model considers that pedestrians' motion can be described as a superposition of several forces. Helbing and Molnár (1) assume that these forces are a combination of psychological and physical forces.

2.2. Pedestrians level of knowledge about the environment

The level of pedestrian's knowledge about the state of the environment in an important element in the route choice process. Pedestrian knowledge concerns his awareness about the number, position and velocity of other pedestrians in the network. This paper will compare three implementations representing different pedestrians' knowledge:

- (i) Pedestrians with full knowledge of the network conditions: In this model pedestrians choose their routes knowing the state of the whole network at all times. This implementation allows the pedestrian to avoid future conflicts, optimizing the route. This model does not reflect the actual decision-making process of pedestrians in real life. Usually a pedestrian has limited knowledge of the network, due to either distance or obstacles.

- (ii) Pedestrians with partial knowledge of the network conditions: This implementation represents the pedestrians' knowledge limitations about the state of the network. A pedestrian only knows the quantity, position and speed of pedestrians who are in his link of the network. Despite the limited knowledge about the network state, the pedestrian completely knows the network geometry and possible paths to his destination. (Figure 1 (ii)).
- (iii) Pedestrians with partial knowledge of the network conditions and memory of past experiences: In spite of having partial knowledge of the network conditions, pedestrians store in their memories the past network conditions of the links already traveled. This implementation limits the knowledge of the pedestrian in the same way as the previous implementation, however, provides to the pedestrian the ability to store past information. (Figure 1 (iii)).

Figure 1 maps the partial knowledge's of the two kinds of pedestrian with partial knowledge, with and without memory. The pedestrians, represented by black circles, had already traveled the path indicated by the dashed arrow.

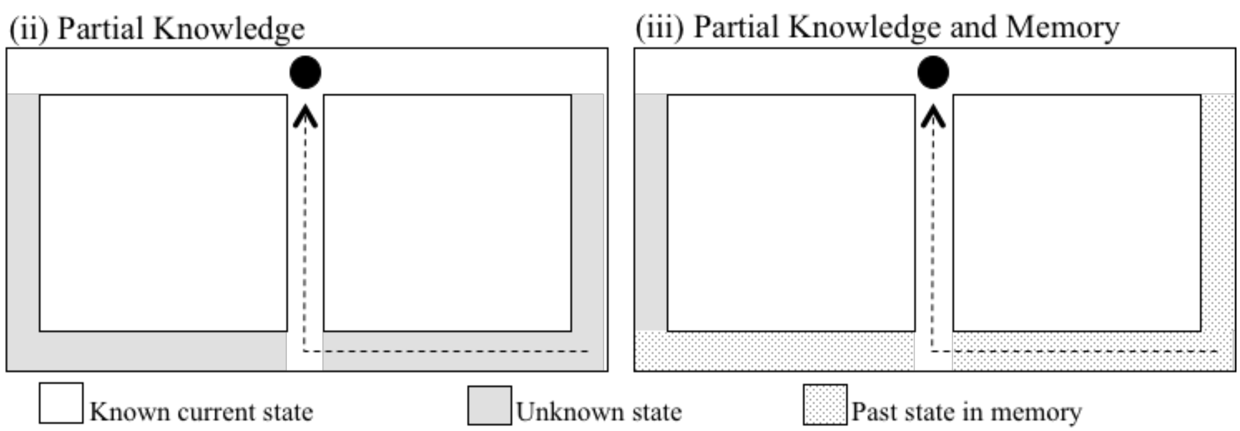


FIGURE 1: Knowledge map over the network.

3. ROUTE CHOICE PROCESS

In this model, the cost of each route is calculated as a function of two factors: route length and the impedance generated by other pedestrians. It is assumed that the impedance generated by the friction between pedestrians exists even before physical contact, due to the psychological tendency to avoid passing close to individuals with high relative velocity (2). Pedestrians seek the route that minimizes length and friction with other pedestrians.

The pedestrian starts the route choice process as soon as he starts the trip. In order to choose the route, the pedestrian takes into account the distance between nodes and also the impedance generated by other pedestrians. Once a route is defined, the pedestrian walks trough this route until he reaches an area of route recalculation or the final destination. An area of route recalculation is any location where pedestrians can choose between two or more alternatives paths.

Dijkistra algorithm (18) is adopted to generate valid paths for any origin/destination pair in the graph. In this formulation, cost is a combination of distance and a term that represents the impedance exerted by other pedestrians in the simulation. The impedance is calculated by the procedure described bellow.

Figure 2 describes a pedestrian α who wants to find a route between nodes *O* and *D* on the graph. The algorithm traverses the graph assigning the cost for each link between the nodes. Figure 2 shows the parameters involved in the calculation of impedance cost between nodes u and n for pedestrian α. The impedance calculation process generates a fictitious pedestrian α' that is positioned on node u and has the desired direction motion, $\vec{e}_{\alpha'}$, oriented to the direction of node n. The fictitious pedestrian has the same attributes of pedestrian α ($\vec{v}^0_{\alpha'} = v^0_\alpha$).

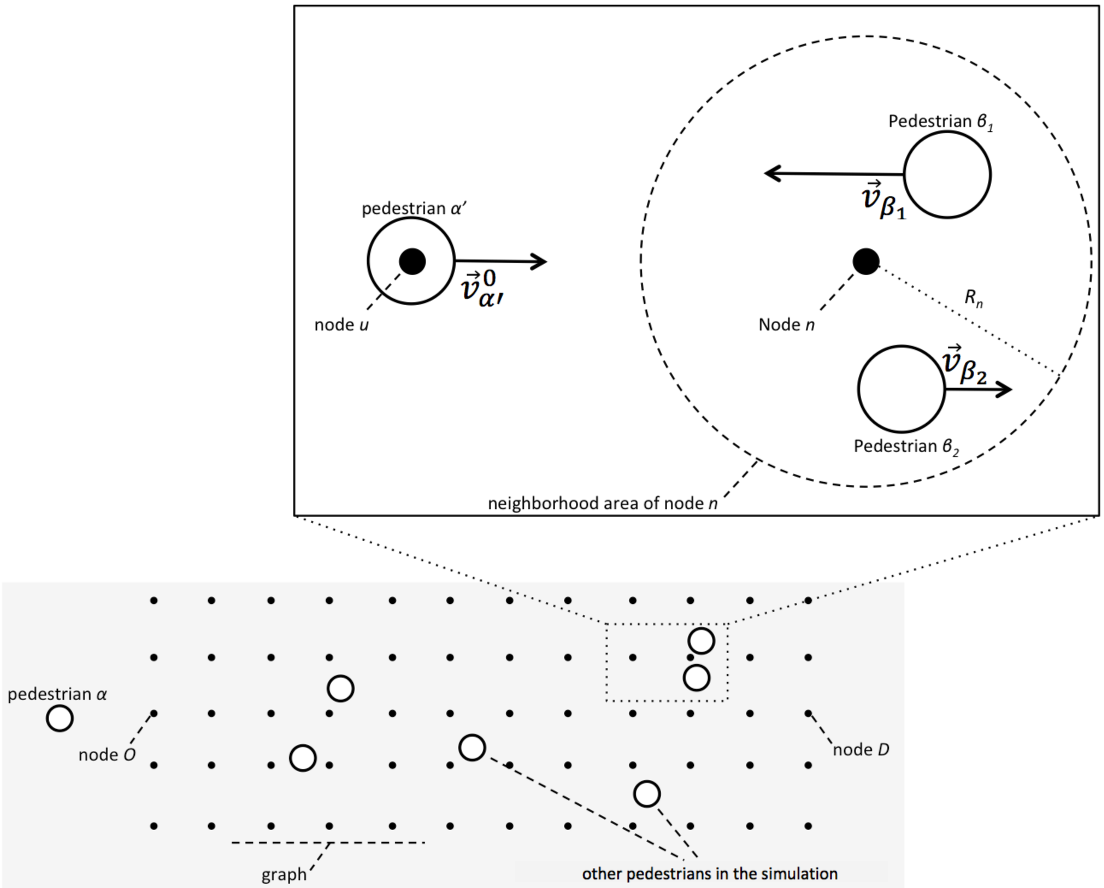


FIGURE 2: The route choice model.

To estimate the impedance exerted over the pedestrian α' it is necessary to know the pedestrian desired velocity, $\vec{v}^0_{\alpha'}$,when he is trying to walk from $\vec{r}_u$ to $\vec{r}_n$:

$$\vec{v}^0_{\alpha'} = \frac{\vec{r}_n - \vec{r}_u}{\|\vec{r}_n - \vec{r}_u\|} . v^0_\alpha \tag{1}$$

In order to calculate the impedance exerted by other pedestrians over α', it is defined a neighborhood area around the graph nodes, with a radius R_n. The impedance is evaluated by the difference between $\vec{v}^0_{\alpha'}$ and the current velocity of other pedestrians β, $\vec{v}_\beta$, walking in neighborhood area. Only pedestrians within the neighborhood area of the node n are considered in the impedance estimation.

Considering each pedestrian β currently in the neighborhood area of the node n, the absolute impedance perceived by the pedestrian α' to walk from u to n, $I_{\alpha'}$, is:

$$I_{\alpha'} = \sum_{\beta} \|\vec{v}_{\beta} - \vec{v}^{0}_{\alpha'}\| \quad [2]$$

The value of $I_{\alpha'}$ is normalized over a settable parameter I_{max}. The cost perceived by the pedestrian α to walk from node u to n, $W^{u,n}_{\alpha}$, is a function of distance and impedance exerted by other pedestrians:

$$W^{u,n}_{\alpha} = \|\vec{r}_{n} - \vec{r}_{u}\|.\,(1 + I_{\alpha'}/I_{max}) \quad [3]$$

The described procedure is repeated until all the possible paths costs are defined. The pedestrian α chooses the route with the lowest cost.

Important aspects about the configuration of the model are the granularity of the graph's nodes and the radius of the neighborhood areas, R_n. If the distance between nodes is too large, the estimation of the impedance generated by the pedestrians' interaction may be poor. On the other hand, if a graph is too dense, the performance of the model can be jeopardized. The radius of the neighborhood area should ideally cover the maximum distance between nodes without overlapping, in order to reduce the probability of over counting or missing pedestrians.

Pedestrians with partial knowledge about network can't estimate the impedance generated by other pedestrians in unknown links of the network. Graph nodes in unknown areas of the network have zero impedance. Pedestrians that have memory can remember the network condition of previously visited links. They store the impedance values previously calculated for each node of the graph. The past network conditions information is accessed only if the current condition is not at an accessible link.

4. SIMULATIONS

The following session presents the results of simulations derived from the implementation of the model described above. The main goal of these simulations was to understand how different levels of awareness of the environment impact on pedestrians' choices and travel times.

The simulation network comprises three blocks (Figure 3). Each corner of the network was numbered from 1 to 8. The length of the horizontal links is 150 m and the length of vertical links is 25 m. Pedestrians present variable desired speed with average value of 1.2 m/s and standard deviation of 0.1 m/s.

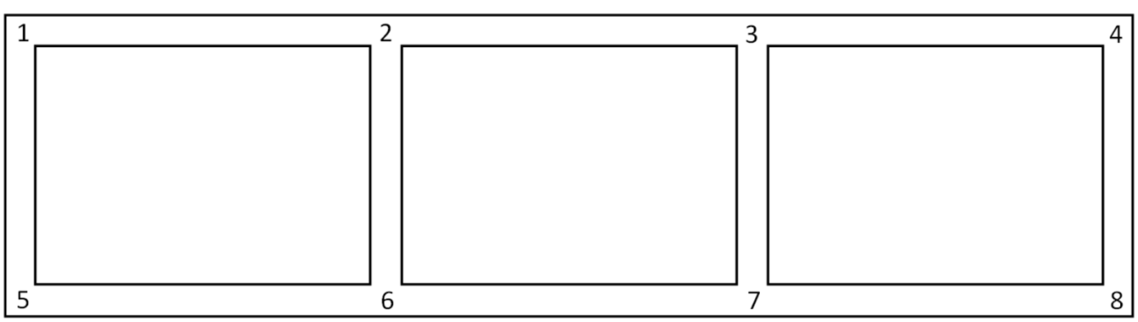


FIGURE 3: Simulation network.

The simulations included two classes of pedestrians: pedestrians with fixed routes that are added to the simulation only to generate some disturb (Disturbing Pedestrians); free will pedestrians that are able to choose routes according to their best ability and knowledge (Study Pedestrians.

Disturbing Pedestrians: these pedestrians do not make a route choice, they are randomly set with one of two possible routes, which are defined by corners: [1, 2, 3, 4, 8] or [1, 2, 6, 7, 8]. They are represented in the simulation by empty circles.

Study Pedestrians: have origin at corner 8 and destination at corner 1. They can follow four possible minimal routes, defined by corners: [8, 4, 3, 2, 1]; [8, 7, 3, 2, 1]; [8, 7, 6, 2, 1]; [8, 7, 6, 5, 1], and several other possibilities, once a pedestrian can opt for a longer route attempting to avoid conflicts with other pedestrians. Study pedestrians are represented in the simulations by black circles.

5. RESULT ANALYSIS

The simulations allowed assessing the performance of the three different pedestrians' knowledge implementations (full knowledge, partial knowledge and partial knowledge with memory). The standard simulation for each implementation involved 70 Study Pedestrians. It was repeated 30 times, totalizing 2100 Study Pedestrians.

The first analysis' stage presents a qualitative analysis of the pedestrians' behavior. The second stage presents a quantitative analysis of travel times and network links traversed on the pedestrians' trip.

5.1. Qualitative Analysis

This analysis aims to assess the overall performance of the three implementations, observing the interaction between pedestrians and the resultant behaviors patterns.

Figure 4 shows two simulations views. Figure 4 (A) shows Study Pedestrians with full knowledge about the network condition. The simulations showed that this assumption may leads to unrealistic behaviors. In this implementation, pedestrians choose routes in order to avoid conflicts that in real situations would be impossible to predict. All the pedestrians chose the same route, avoiding the network link between corners 1 and 2, the most loaded by the Disturbing Pedestrians. Figure 4 (B) shows pedestrians with partial knowledge of the network. This simulation provides grater interaction between pedestrians, seeming more natural, befitting real situations.

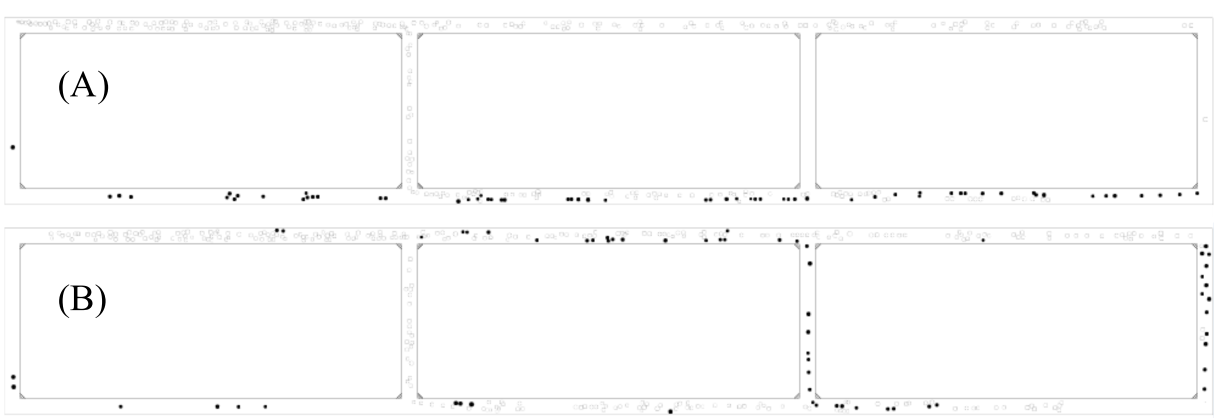


FIGURE 4: Simulation views.

The implementation of pedestrians with partial knowledge and no memory also leads to unrealistic behaviors. Sometimes pedestrians find themselves in a deadlock situation, trying to find a less congested link. Figure 5 illustrates a typical deadlock situation experienced by a Study Pedestrian that wants to reach destination avoiding unnecessary conflicts with others. At the state "A", the pedestrian decides to follow the dashed arrow to reach the destination. Reaching the corner, at the state "B", he faces another conflicting group, deciding to return on the same link, on the opposite direction, reaching the same position on the state "A".

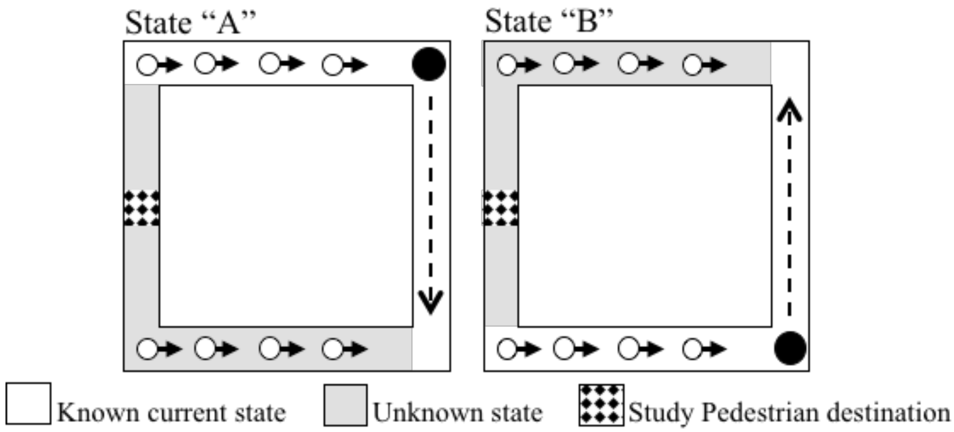


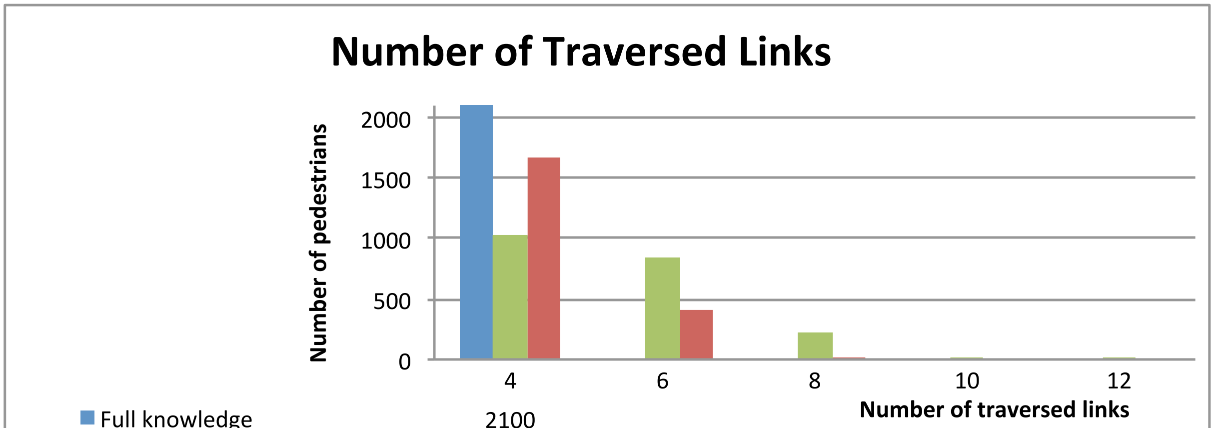
FIGURE 5: Pedestrian deadlock.

The deadlock situation, presented in the Figure 5, was purged with the pedestrians' memory implementation. In this implementation, for example, the pedestrian at the state "B" would remember that the top link was also congested and could decide to face the pedestrians at the bottom link, once he is already there.

5.2. Quantitative Analysis

The quantitative analysis aims to evaluate the impact of the three different implementations on route length and travel times.

Figure 6 shows the number of network links the pedestrians traverse during the entire trip. The minimal number of links that pedestrians should travel to reach their destination is 4. All pedestrians with full knowledge choose only minimal length routes, since they don't make any misjudgment trying to find a less congested branch. Pedestrians with partial knowledge about traffic conditions, and with no memory, sometimes oscillate into the deadlock situation previously described, traversing a large number of unnecessary links. The simulation results show that, although some pedestrians with memory use non-minimal length routes, they do not present deadlock oscillation.



	4	6	8	10	12
Full knowledge	2100				
Partial knowledge	1026	835	215	22	2
Partial knowledge with memory	1679	416	5		

FIGURE 6: Traversed links.

The travel time distribution shows that there are expressive differences between the three pedestrians implementations. Pedestrians with full knowledge of the network present the lowest travel times and standard deviation (average travel time of 361 seconds and standard deviation of 27 s). Pedestrians with partial knowledge, and no memory, had the highest travel times and standard deviation. The average value was 416 seconds and standard deviation 60 seconds. The simulation results of pedestrians with partial knowledge and memory, present intermediate travel times values between the two previous implementations. The average travel time was 379 seconds and the standard deviation was 37 seconds. The Figure 7 illustrates the travel times values obtained in the three implementations.

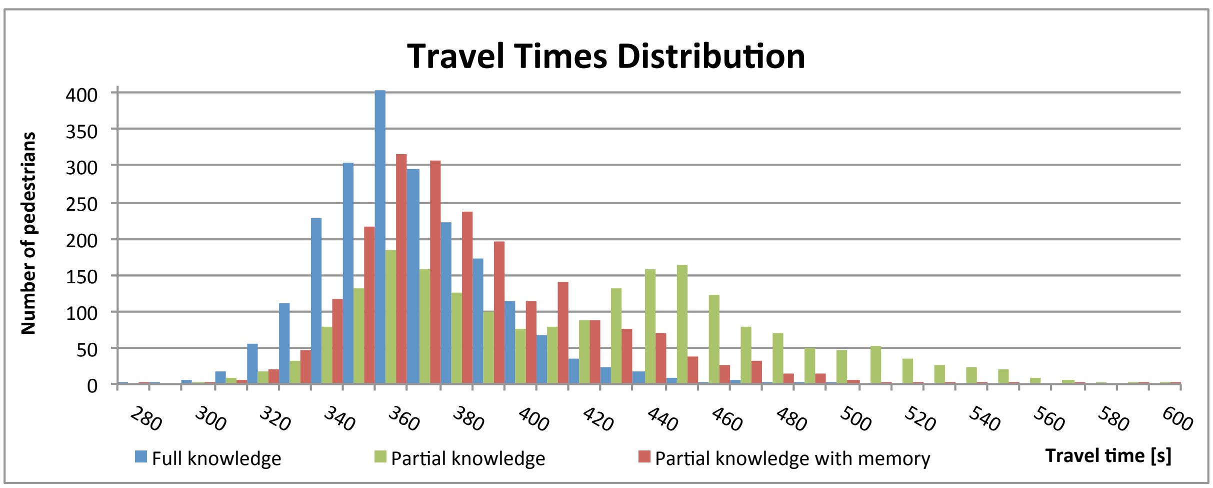


FIGURE 7: Travel time distribution.

6. CONCLUSIONS

The modeling approach presented in this paper provides a sound representation of pedestrian route choice dynamics. Route choice is based on a combination of distance and the impedance generated by other pedestrians, adopting a pedestrian friction concept to calculate impedance. This concept proved to be capable to support additional heuristics, allowing its application in different route choice contexts. This paper presents three different levels of the pedestrian's knowledge about the state of the network (full knowledge, partial knowledge and partial knowledge with memory). Performed simulations revealed that the level of pedestrians' knowledge about the state of the network has an important role on the results.

Route choices made by pedestrians with complete knowledge about the network state present the shortest distance and travel times. According to this approach pedestrians adopted the best possible route choice, regarding the combination of length and conflict avoidance for the whole trip. Most models in the literature assume this hypothesis. However, the decisions made by these pedestrians seemed unrealistic. In real life, pedestrians can't predict conflicts in advance as observed in the simulations, especially in large networks. This approach underestimates the pedestrians' travel times.

Most real pedestrians have partial knowledge about the network state, therefore, this paper presents an implementation that represents this limitation. However, the limited knowledge of the pedestrians also led into unrealistic behaviors, as the deadlock oscillation, let to unnecessary longer routes resulting in overestimated pedestrians' travel times.

The third implementation attempted to get even closer to the actual pedestrians decision-making process by the memory implementation. The pedestrians with limited knowledge about the network and a memory of past experiences presented the more reasonable behaviors under congested conditions. This implementation solved the problems observed on the previous ones, resulting in intermediate travel time's values. The route choice of pedestrian with partial knowledge and memory is more similar to the real life decision process, where pedestrians have partial knowledge of the environment and keep in memory the state of the places previously visited. The similarity of the real life process led to the sounder results between the three proposed implementations.

The pedestrians' implementation with partial knowledge and memory of past experiences can be extended to a wide range of situations. The model is suitable to represent urban environments and any other places where the people density can influence the pedestrians' route choice.

ACKNOWLEDGEMENTS

Acknowledgements for the National Council for Scientific and Technological Development (CNPQ) and National Council for the improvement of Higher Education (CAPES) for the financial support.

REFERENCES

(1) HELBING, D.; MOLNAR, P. Social force model for pedestrian dynamics. Physical Review E 51, p. 4282–4286, 1995.

(2) HELBING, D.; JOHANSSON, A. Pedestrian, Crowd and evacuation dynamics. Swiss Federal Institute of Technology, 2009.

(3) HELBING, D.; FARKAS, I; VICSEK, T. Simulating dynamical features of escape panic. Nature 407, 487-490, 2000.

(4) SUMPTER, D. The principles of collective animal behaviour. Phil. Trans. R. Soc. B 361, 5–22, 2006.

(5) MILGRAM, S.; TOCH, H. Collective behavior and social movements. Handbook of social psychology, 2nd ed, Vol. IV, 507-610, 1969.

(6) TEKNOMO, K. Modeling mobile traffic agents on network simulation. Proceedings of the 16th Annual Conference of Transportation Science Society of the Philippines (TSSP), Manila, 2008.

(7) HILL, M. R. Spatial structure and decision-making of pedestrian route selection throught an urban envorironment, Ph.D Thesis, University Miocrofilms International, 1982.

(8) SENEVARANTE, P.N.; MORALL, J. Analysis of factores affecting the choice of route of pedestrians. Transportation Planning and Technology 10, 147-159, 1986.

(9) KIRIK, E. S.; YURGEL'YAN, T. B.; KROUGLOV, D. V. The shortest time and/or the shortest path strategies in a CA FF pedestrian dynamics model. Journal of Siberian Federal University. Mathematics & Physics, 2, 271–278, 2009.

(10) DRESSLER, D., GROß, M.; KAPPMEIER, J.; KELTER, T.; KULBATZKI, J.; PLU˙MPE, D.; SCHLECHTER, G.; SCHMIDT, M.; SKUTELLA, M.; TEMME, S. On the use of network flow techniques for assigning evacuees to exits. Procedia Engineering, 3, 205–215, 2010.

(11) LÄMMEL, G.; PLAUE, M. 2012. Getting out of the way: collision avoiding pedestrian models compared to the real world. Pedestrian and Evacuation Dynamics, 2012.

(12) PAPADIMITRIOU, E. Theory and models of pedestrian crossing behaviour along urban trips. Transportation Research Part F: Traffic Psychology and Behaviour, 15, 75-94, 2012.

(13) KRETZ, T., GROßE, A.; HENGST, S.; KAUTZSCH, L.; POHLMANN, A.; VORTISCH, P. Quickest paths in simulations of pedestrians. Advances in Complex Systems 14.05, 733-759, 2011.

(14) PATIL, S.; BERG, J.; CURTIS, S.; LIN, M.; MANOCHA, D. Directing crowd simulations using navigation fields, IEEE Transactions on Visualization and Computer Graphics, 244-254, 2010.

(15) TREUILLE, A.; COOPER, S.; POPOVIĆ, Z. Continuum crowds. ACM Transactions on Graphics (TOG), 25. No. 3. ACM, 2006.

(16) WAGOUM, A. U. K.; SEYFRIED, A.; HOLL, S. modeling the dynamic route choice of pedestrians to assess the criticality of building evacuation. Advances in Complex Systems, 15.07, 2012.

(17) GAUD, N.; GALLAND, S.; GECHTER, F.; HILAIRE, V.; KOUKAM, A. Holonic multilevel simulation of complex systems: Application to real-time pedestrians simulation in virtual urban environment. Simulation Modelling Practice and Theory, 16, 1659–1676, 2008.

(18) DIJKSTRA, E. W. A note on two problems in connexion with graphs. Numerische Mathematik 1: 269–271, 1959.

4. THIRD PAPER

“Calibration of a Pedestrian Route Choice Model With a Basis in Friction Forces” [19]

CALIBRATION OF A PEDESTRIANS' ROUTE CHOICE MODEL BASED IN FRICTION FORCES

Bruno Rocha Werberich, Ms.

Research, Department of Production Engineer, Federal University of Rio Grande do Sul, Porto Alegre, Brazil. Tel +55 (51) 33083596, Fax +55 (51) 33084007, Av Osvaldo Aranha 99, 5 andar. E-mail: bruno.rwe@gmail.com.

Carlos Oliva Pretto, Dr.

Research, Department of Production Engineer, Federal University of Rio Grande do Sul, Porto Alegre, Brazil. Tel +55 (51) 33083596, Fax +55 (51) 33084007, Av Osvaldo Aranha 99, 5 andar. E-mail: cpretto@gmail.com.

Helena Beatriz Bettella Cybis, PhD.

Associate Professor, Department of Production Engineer, Federal University of Rio Grande do Sul, Porto Alegre, Brazil. Tel +55 (51) 33083596, Fax +55 (51) 33084007, Av Osvaldo Aranha 99, 5 andar. E-mail: helenabc@producao.ufrgs.br.

Word count:	5,064 (7500 maximum)
Tables and figures:	2,250 (9*250 words each table or figure)
Total words:	7,314

ABSTRACT

This paper presents a pedestrian route choice model and its calibration with real data. The model explicitly represents interaction between pedestrians as an impedance force influences pedestrians route choice. This model approach is inspired by friction forces equations, considering pedestrians avoid passing near other pedestrians with high relative velocity. Route choice process is a function of impedance force and route length. Social force model was used to model pedestrians walking behavior. Calibration was based on data acquired from a real experiment developed in a simplified network. Data collection was based on video analysis. The paper presents and discusses results from calibration processes. This model differs from others pedestrians' route choice model because it seamlessly incorporate pedestrians social force model into route choice decision process.

Keywords: route choice, model calibration, social force, pedestrian simulation, pedestrian behavior.

1. INTRODUCTION

Simulation of pedestrians is a complex task. In order to represent motion of pedestrians more realistically, models are required to simulate several processes, including sense and avoidance of obstacles, interaction with other pedestrians and route choice. Social force model has been successful in reproducing various observed phenomena on pedestrian simulation. Collective behaviors frequently emerge from interactions among individuals, such as shock waves in dense crowds, lanes of uniform walking directions in pedestrian counter flows, circulating flows at intersections or oscillating flows at bottlenecks [1][2][3]. This phenomenon, also called self-organization, is an emergent behavior arises from interactions between agents. Studies of self-organization in pedestrian crowds include pedestrian streams in corridors or alleys [4][5][6] and movement of pedestrians through a waiting crowd [5][7]. More complex studies consider escape of disoriented people from a room [8]. Understanding pedestrians´ behavior and how routes are chosen is essential for planning and designing public and private infrastructures.

Majority of pedestrians' models can be classified into two categories: (i) models where pedestrians/agents don't have imbedded route choice algorithms (route choice process can or cannot emerges from simulation) and; (ii) models where agents have imbedded route choice algorithms [9].

Selection of alternative routes in the first category happens as self-organization phenomena. This phenomenon is an emergent behavior arises from interaction between agents. These models are not suitable for wide-open spaces and complex urban networks.

Models from the second category present explicit route choice capabilities. Pedestrians adopt some sort of function to find routes to destination. These models can present static or dynamic route choice process. Static route choice models are built on the assumption pedestrians walk along shortest route, defined before the trip starts, and try to walk through this route while avoiding collisions. Dynamic route choice models differ from their static counterparts on the sense they represent route changes over time. They aim to provide a sounder representation of route choice process, emulating behavior of individual pedestrians while considering variations in the environment.

Several walking processes, such as route selection strategies, are based on subconscious decisions. Perception of distance and directness are the most common reasons for choosing a particular route [10]. Pedestrians frequently choose the shortest route, although they are not aware of this utility maximization process [11]. Most models presented in the literature are concerned only with the quickest or shortest route, like Kirik *et. al*. [12], Dressler *et. al*. [13] and Lämmel *et. al*. [14]. However, other factors play an important role in route choice behavior, such as: peoples' habits, number of crossings, pollution, noise levels, safety, shelter from poor weather conditions and stimulations of the environment [15].

Most relevant route choice models are concerned with pedestrians' evacuation. In Kretz *et. al.* [16], for example, pedestrians routes are chosen based on the minimal remaining travel time to the destination. Patil *et. al*. [17] propose an interactive algorithm to direct and control crowd simulations. Model presented by Treuille *et. al*. [18] unifies route planning and local collision avoidance by using a set of dynamic potential and velocity.

Teknomo [9] and Teknomo *et al*. [19] described an approach based on route choice self-organization to model the dynamics of mobile agents, such as pedestrians and cars on a simple network graph. This modeling approach is based on the route choice self-organization of multi agents. The agents decide, when reaching a vertex, which edge to enter next. This decision is based on a set of rules regarding the agent's observation of the local environment. The model simulates only one-directional movement from the origin to the destination vertex. In order to represent complex networks, such as urban scenarios, models need to include route choice capabilities.

Calibrating a pedestrian route choice model is a complex task mainly for two reasons: (i) Many factors interfere on pedestrians route choice, (ii) data collection is difficult. In real environments, pedestrians may change routes for many reasons not subject of this study, as pavement conditions, safety, the presence of stores, and others. [15]. Tracking pedestrians along real outdoor and indoor environments is difficult due to limited view of the modeled environment.

There are many different technologies regarding data collection of pedestrians. However, the manual data collection and the computer vision are the most common in the literature [20]. Some authors use video images of pedestrians recorded on a controlled environment [21][22][23]. This approach enables the study of a particular variable of interest without disturbs of other uncontrollable environment variables. In a controllable environment, the automatic detection and tracking of a pedestrian is easier due to facilities of positioning video cameras with a good view and the possibility to use colored markers for pedestrians' identification.

A pedestrian model calibration comprises several aspects. There are measurable variables as speeds, observable elements as avoidance of obstacles and other pedestrians and also behavioral aspects related to route choice preferences. The overall behavior and patterns of moving can be extracted by some measures as travel times, counting pedestrians and average speeds [24]. Schönauer *at al.* [25] represent the speed of pedestrians, bicycles and vehicles over a real environment using a color scale forming a heat map. The generated map characterizes the environment and allows comparisons between the collect data and simulation analysis.

This paper presents a dynamic route choice model based on a combination of distance and impedance generated by other pedestrians [26]. The calculation of the impedance is derived from friction concept proposed by Helbing and Johansson [1]. The impedance generated by friction equations involve variables related to pedestrian's profile like the desired speed and other pedestrians' velocity. We develop a real data collection experiment to calibrate the proposed model. The results show model soundly represents the pedestrians' route choice process.

2. THE MODEL

An agent-based model is proposed to address the pedestrian route choice problem. Agent-based models represent agents' decision-making ability based on agents' characteristics profile and perception over the environment. In the proposed model, pedestrians are agents able to choose and recalculate routes. Pedestrians are not assigned to predetermined routes.

In this model, a route is a set of coordinates followed by a pedestrian form origin to destination. The route choice process comprises distance and the interaction with other pedestrians. Route choice looks upon pedestrians' ability to avoid crowded areas and conflicting flows. The proposed approach allows the definition of several origins-destination pairs, reproducing real urban environments, like transportation stations, buildings, parks and others.

The aggregation of different levels of abstraction on a simulation model is a complex task. In most cases, each level of abstraction can be separately modeled on a multi-layer simulation approach [27][28][29]. The framework adopted to describe pedestrian behavior in this model (Figure 1) presents a three-layer structure, each layer representing:

(i) demand for travel: set of origin and destination;

(ii) structure of simulation environment: set of nodes composing the simulation graph;

(iii) pedestrians movement, sense and avoidance of obstacles: set of equations and agents behavior rules.

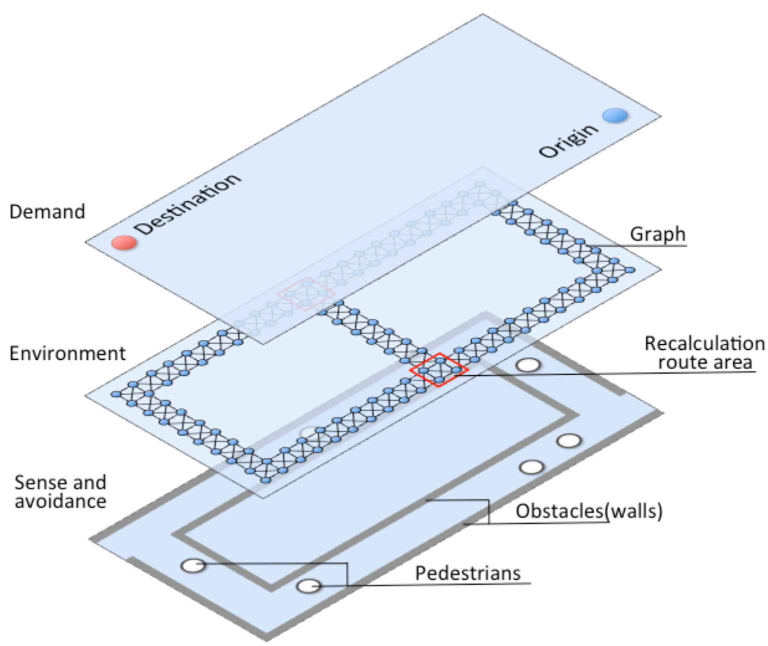


Figure 1 – Multi-layer model

2.1. Demand configuration

Each origin-destination pair is associated to a number of trips and a pedestrian generation rate. Origins and destinations are associated with the nearest nodes from the graph on the environment layer. A graph is a set of objects where some pairs of objects are connected by links. The interconnected objects are represented by mathematical abstractions called nodes. Nodes are defined as a pair of coordinates (*x,y*) in the simulation environment.

2.2. Environment configuration

The environment is described as a continuous space and is composed by geometric entities, such as rooms, doors, and other obstacles. The environment entities are linked by a graph-based structure. The graph provides a route to all entities. The graph generation process should guarantee no edge of the graph intersects any walls or obstacles.

This layer also contains route recalculation areas where a pedestrian can choose between alternative routes. The role of recalculation areas will be discussed later.

2.3. Pedestrian movement

The social force model [1] describes pedestrian walking behavior regarding the agents' low-level motion, collision avoidance and velocity adaptation. The social force model considers pedestrians' motion can be described as a superposition of several forces. Helbing and Molnár [6] assume these forces are a combination of psychological and physical forces. Pedestrians freely walk on the modeling environment seeking the next graph node of the designated route. Pedestrians' movements are ruled by the sense and avoidance model and are not restricted to a strict set of links.

A pedestrian α who wants to reach his destination $\vec{r}_\alpha^0$ takes the shortest possible route. The pedestrian's trip will usually have some intermediate destinations, $\vec{r}_\alpha^1 \ldots \vec{r}_\alpha^k$. Assuming $\vec{r}_\alpha^k$ is the next partial destination, the desired direction of motion $\vec{e}_\alpha(t)$, according Helbing and Molnár [1], will be:

$$\vec{e}_\alpha(t) = \frac{\vec{r}_\alpha^k - \vec{r}_\alpha(t)}{\|\vec{r}_\alpha^k - \vec{r}_\alpha(t)\|} \tag{1}$$

Where $\vec{r}_\alpha(t)$ denotes the pedestrian's α position at time t.

Any pedestrian α presents a desired speed v_α^0 and a desired direction $\vec{e}_\alpha$. The desired velocity is, therefore, $\vec{v}_\alpha^0(t) = v_\alpha^0\vec{e}_\alpha(t)$.

In case of deviations from the desired velocity, the pedestrian assume a current velocity $\vec{v}_\alpha(t)$. The pedestrian α tends to restore $\vec{v}_\alpha(t)$ within a certain relaxation time τ_α. Helbing and Molnár [1] describe this adaptation by the acceleration term $\vec{F}_\alpha^0$:

$$\vec{F}_\alpha^0(\vec{v}_\alpha, v_\alpha^0\vec{e}_\alpha) = \frac{1}{\tau_\alpha}(v_\alpha^0\vec{e}_\alpha - \vec{v}_\alpha) \tag{2}$$

Pedestrians feel uncomfortable close to other pedestrians and walls; therefore, the presence of pedestrian β will result in a repulsive force affecting the motion of pedestrian α. Helbing and Molnár [1] represent this effect by $\vec{f}_{\alpha\beta}$:

$$\vec{f}_{\alpha\beta}(\vec{r}^{\alpha\beta}) = -\nabla_{\vec{r}_{\alpha\beta}} V_{\alpha\beta}[b(\vec{r}_{\alpha\beta})] \tag{3}$$

Where $V_{\alpha\beta}$ is the repulsive potential, represented by a monotonic decreasing function with equipotential elliptical lines. The elliptical shape reproduces the pedestrian's need for more space in the direction of motion. b is the semi-minor axis of the pedestrian ellipse defined by $\vec{r}_{\alpha\beta}$ ($\vec{r}_{\alpha\beta} = \vec{r}_\alpha - \vec{r}_\beta$). The resultant force exerted over a pedestrian is a superposition of three forces:

the force to adapt the current velocity to the desired velocity ($\vec{F}_{\alpha}^{0}$), the forces exerted by other pedestrians ($\vec{f}_{\alpha\beta}$), and the forces exerted by walls and other obstacles.

3. ROUTE CHOICE PROCESS

In this model, the cost of each route is calculated as a function of two factors: route length and the impedance generated by other pedestrians. The impedance generated by the friction between pedestrians is assumed to exist even before physical contact, due to the psychological tendency to avoid passing close to individuals with high relative velocity [1]. Pedestrians seek minimal route length and minimal friction with other pedestrians.

The pedestrian starts the route choice process as soon as he starts the trip. In order to choose the route, the pedestrian takes into account the distance between nodes and also the impedance generated by other pedestrians. Once a route is defined, the pedestrian walks trough this route until he reaches an area of route recalculation or the final destination. An area of route recalculation is any location where pedestrians can choose between two or more alternatives routes.

Dijkistra algorithm [30] is adopted to generate valid routes for any origin/destination pair in the graph. In this formulation, cost is a combination of distance and impedance exerted by other pedestrians in the simulation. The impedance is calculated by the procedure described bellow.

Figure 2 describes a pedestrian α who wants to find a route between nodes O and D on the graph. The algorithm traverses the graph assigning the cost for each link between the nodes. Figure 2 shows the parameters involved in the calculation of impedance cost between nodes u and n for pedestrian α. The impedance calculation process generates a fictitious pedestrian α' positioned on node u and has the desired direction motion, $\vec{e}_{\alpha'}$, oriented to the direction of node n. The fictitious pedestrian has the same attributes of pedestrian α ($\vec{v}_{\alpha'}^{0} = v_{\alpha}^{0}$).

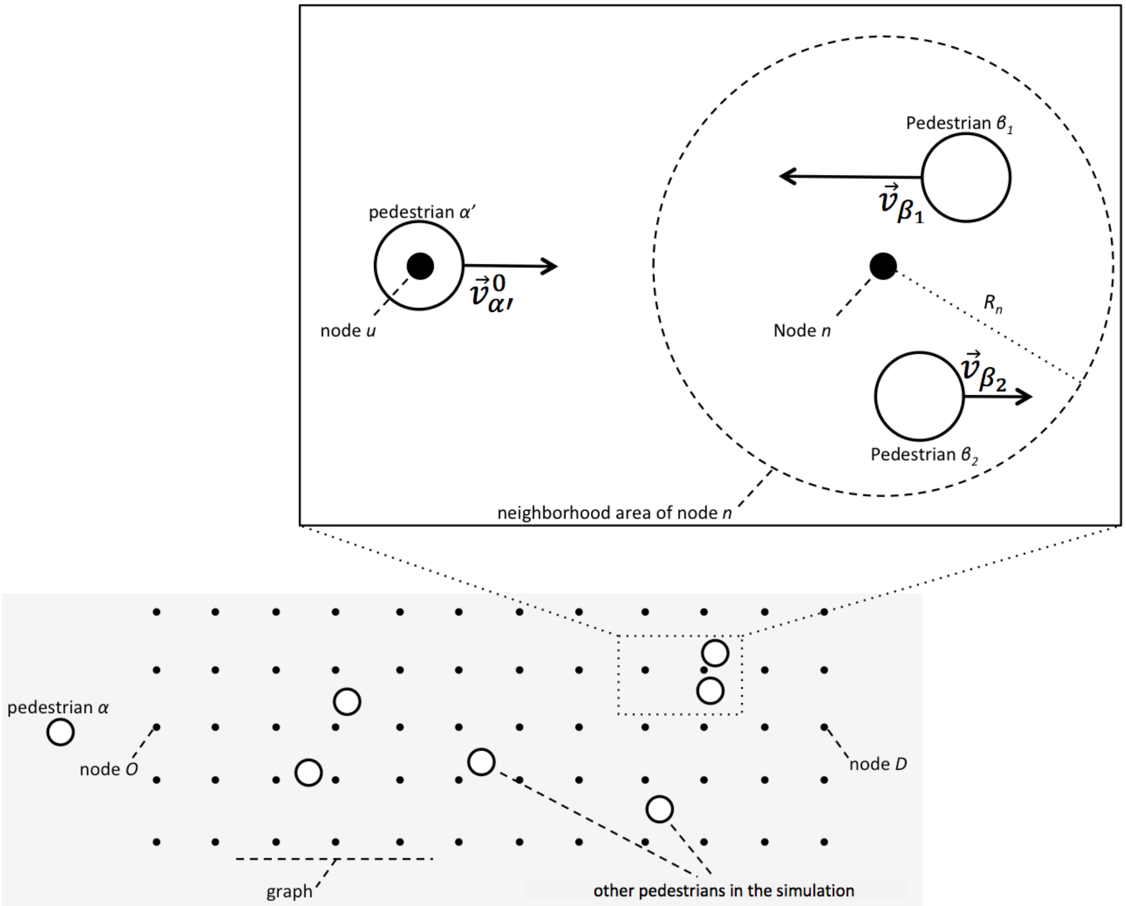


Figure 2 - The route choice model

To estimate the impedance exerted over the pedestrian α' it is necessary to know the pedestrian desired velocity, $\vec{v}^{0}_{\alpha'}$,when he is trying to walk from $\vec{r}_u$ to $\vec{r}_n$

$$\vec{v}^{0}_{\alpha'} = \frac{\vec{r}_n - \vec{r}_u}{\|\vec{r}_n - \vec{r}_u\|} . v^{0}_{\alpha} \quad (4)$$

In order to calculate the impedance exerted by other pedestrians over α', it is defined a neighborhood area around the graph nodes, with a radius R_n. The impedance is evaluated by the difference between $\vec{v}^{0}_{\alpha'}$ and the current velocity of other pedestrians β, $\vec{v}_{\beta}$, walking in neighborhood area. Only pedestrians within the neighborhood area of the node n are considered in the impedance estimation.

Considering each pedestrian β currently in the neighborhood area of the node n, the absolute impedance perceived by the pedestrian α' to walk from u to n, $I_{\alpha'}$ is:

$$I_{\alpha'} = \sum_{\beta} \|\vec{v}_{\beta} - \vec{v}^{0}_{\alpha'}\| \quad (5)$$

The value of I_{α}, is normalized over a settable parameter I_{max}. The cost perceived by the pedestrian α to walk from node u to n, $W_{\alpha}^{u,n}$, is a balance between distance and the impedance exerted by other pedestrians:

$$W_{\alpha}^{u,n} = \|\vec{r}_n - \vec{r}_u\|.(1 + I_{\alpha}/I_{max}) \qquad (6)$$

The described procedure is repeated until all possible routes costs are defined. Pedestrian α chooses the route with the lowest cost. The algorithm adopted to calculate the motion cost for pedestrian α' from node u to n is presented below:

```
Double Cost_from_node_u_to_n(Node u, Node n, Pedestrian A)
{
 Double Absolute_Impedance = 0;
 Vector vA = Normalize(n.position - u.position) * A.DesiredVelocity;
 Q = List with all Pedestrians in the simulation;

 foreach Pedestrian B in Q
    if(DistanceBetween(B, n) < n.NeighborhoodRadius)
        Absolute_Impedance += Module(B.currentVelocity - vA);
    end if;
 endforeach;

 return Module(n.position - u.position) * (1 + Absolute_Impedance/ Max_Impedance);
}
```

One important aspect of model configuration is the distance between the graph nodes. The radius of neighborhood areas (R_n) is defined as half distance between nodes. Impedance measures associated to nodes neighborhood areas emulate pedestrians' sensors. Distance between nodes must be defined in order to reduce missing pedestrians. If distance between nodes is too large the impedance estimation could not capture real pedestrians' organization. On the other hand, if a graph is too dense, models performance can be jeopardized due to computation costs.

I_{max} (Equation 6) is a key parameter in the calculation of the cost perceived by pedestrians (W). This parameter acts as weighting factor between travel distance and the perceived impedance. The higher the value of Imax, the lower the willingness of pedestrians to choose an alternative longer route. The I_{max} is a calibration parameter adjusted to reflect the willingness of pedestrians to trade for longer routes, depending on pedestrian's density on the shortest route. More details about the calibration process are presented in Section 6.

3.1 Pedestrians level of knowledge about the environment

The pedestrian's level of knowledge about the state of the environment in an important element in the route choice process. Pedestrian knowledge concerns his awareness about the number, position and velocity of other pedestrians in the network. In this study, was considered pedestrians have partial knowledge of the network conditions and memory of past experiences. During a simulation period, pedestrians keep in memory the past conditions of the links already traveled. The memory is available for one simulation only. When another simulation is started, the pedestrians have their memory reset. Werberich et al. [31] describe the memory process in more details.

4. EXPERIMENT

In order to obtain data to calibrate the model a route choice experiment on a simplified network was developed. The experiment was set up inside the university campus. The network built for the experiment had 2-meter-high walls and two opposite entrances. Figure 3 shown the scenario layout presenting detailed measurements and corners numbers from 1 to 8. The main goal of this experiment is to collect data related to the pedestrians' route choice behavior in a congested network. For this analysis, volunteer students walked inside the scenario as if they were in a real environment.

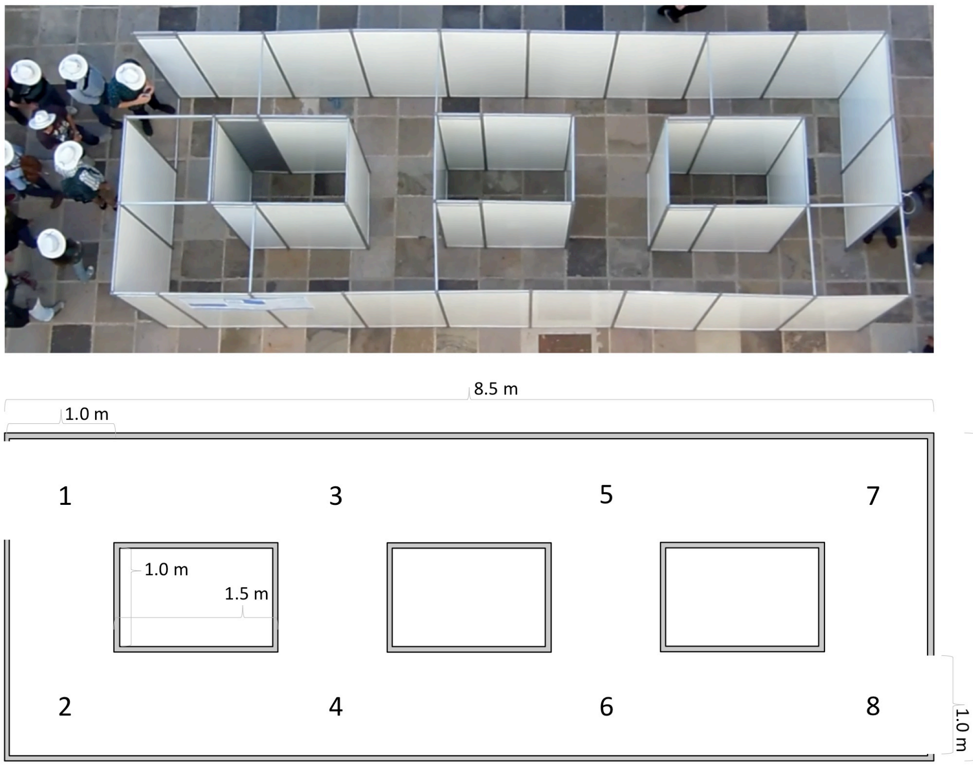


Figure 3 –Experiment layout

Forty pedestrians were split into two groups of twenty pedestrians to perform the data collection. The first group walked from the entrance in corner 1 to the exit at corner 8. The other group walked into the opposite direction (corner 8 to 1). The first group was instructed to follow a fixed route. The fixed route was defined by corners {1 – 3 – 4 – 6 – 8}. The other group had no specific orientation about routes. They were free to choose any route from entrance to exit. We call these two groups by the fixed route group and the free route group, respectively. Figure 4 shows images of the experiment. White hats identify the fixed route group and black hats the free route group.

Data was collected by video recording. The camera was set at approximately 15m high with a top view to capture the video images.

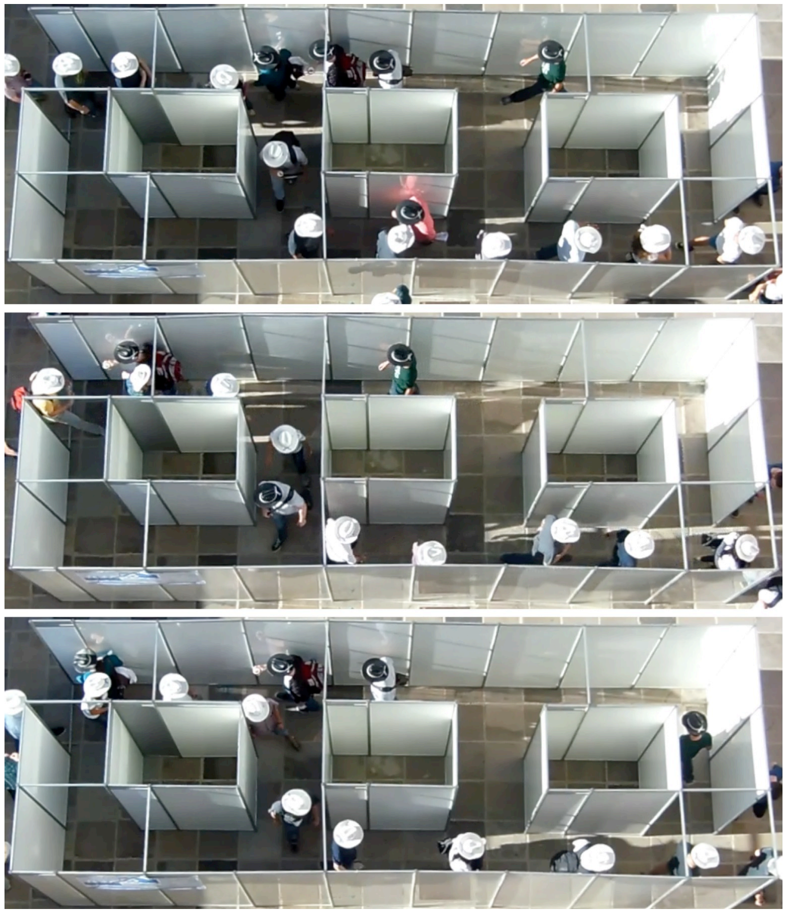


Figure 4 – Running the Experiment

The average entrance rate for the fixed route pedestrians is 2 seconds, for free route pedestrians 5 seconds. The large interval time for the free route pedestrians' entrance ensures they make their decisions observing the environment, not simply following the previous pedestrian.

The video analysis was made with the aid of software called Tracker [32]. Its main features include object tracking with position, velocity and acceleration, special effect filters, multiple reference frames and calibration points. The data collection was a semi-automatic process for video analyses. The data were collected independently for each pedestrian in the experiment. The software collected a position (x, y) for a pedestrian at each video frame; the video was recorded with 30 fps. Figure 5 shows the route for all pedestrian in the free route group. The black dashed line represents the fixed route. In the density colored map of pedestrians (figure 5) the blue color represent areas with no pedestrians and red colors represent areas with higher presence of pedestrians. The same color map was used in the calibration process for a visual feedback.

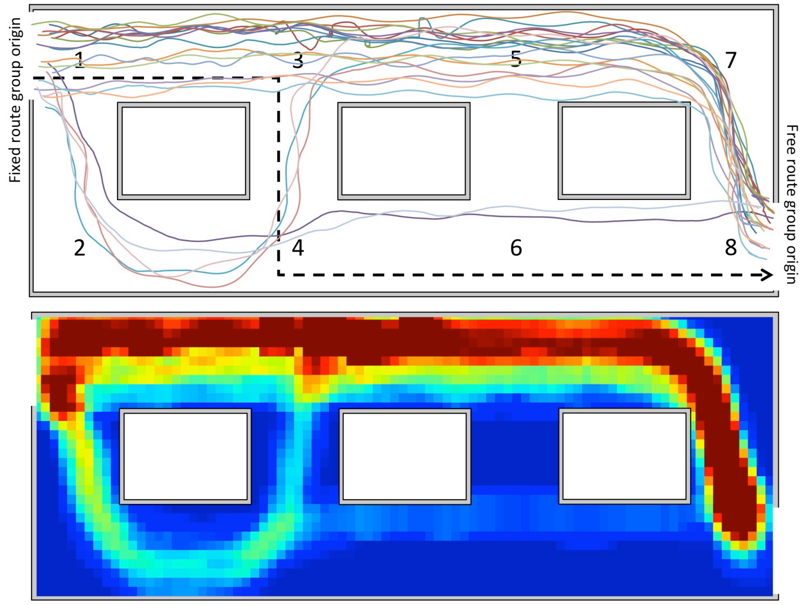


Figure 5 – Collected Data

The average travel time for the free route group in the experiment was 12.8 seconds with a standard deviation of 3.6 seconds. The average distance traveled was 10.6 meters with standard deviation of 0.89 meters.

5. SIMULATIONS

The following session presents the results of simulations derived from the implementation of the model described above.

The experiment layout and graph granularity adopted in the simulation network is presented in Figure 6. The distance between nodes is 1.0m and the R_n value is 0.5m.

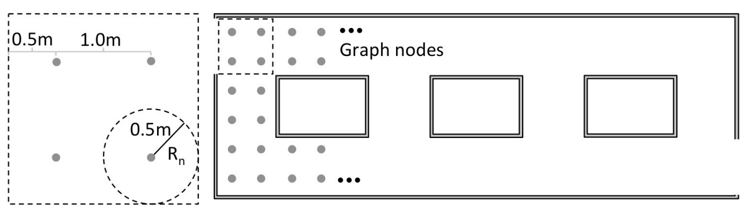


Figure 6 – Simulation Graph

Pedestrians were generated with variable desired speed with average value of 1.0 m/s and standard deviation of 0.1 m/s. Similarly to the experiment, the simulations included two classes of pedestrians: pedestrians with fixed route and free route pedestrians. Pedestrians generation rate of the fixed route group was 1 pedestrian at each 2 seconds. The generation rate of the free route group was 1 pedestrian at each 5 seconds.

5.1. Calibration

The first step of the calibration process was the adjustment of the social force model parameters. The calibration of the social force model allows the correct representation of the repulsive forces from obstacles and pedestrians. The parameters of the social force model used in this experiment were similar to those presented in Helbing and Molnár [1].

The key parameter for the calibration of the route choice process is I_{max} (Equation 6). This parameter is a weighting factor between travel distance and the perceived impedance. The higher the value of I_{max}, the lower the willingness of pedestrians to choose an alternative longer route. For the goals of this paper, the main calibration method was similar to Johansson et al. [33] where a microscopic simulation model was applied and calibrated by using pedestrian route data. Figure 7 shows the results of five simulations with different I_{max}values {0.3, 0.6, 0.9, 1.2, 1.5}. The increment of 0.3 in I_{max} value was chosen as the minimal value showed a significant influence in the simulation outcomes. Density color map, average travel time and average distance traveled were adopted as calibration references to identify the best fit for the experiment data. Figure 6 shows the density color map, average distance traveled and average travel time for each I_{max} value, for free route pedestrians.

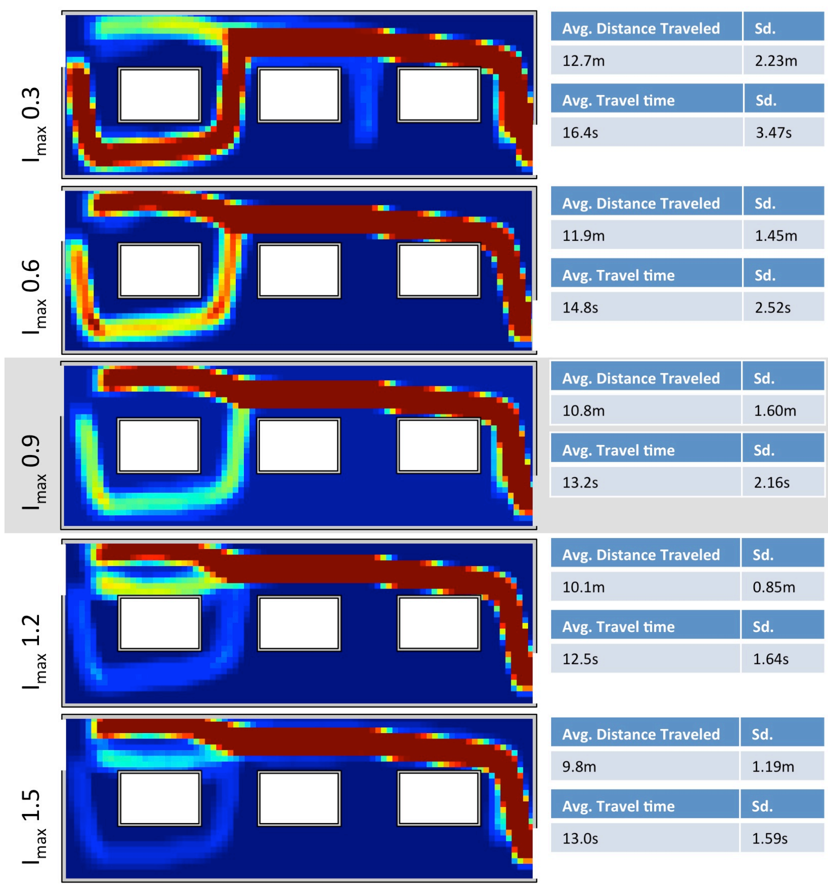


Figure 7 – Calibration Process

5.2. Results

In this case study, $I_{max} = 0.9$ was defined as the best fit to calibrate the model. The average travel time of free route pedestrians in the experiment was 12.8 seconds with a standard deviation of 3.6 seconds. The average distance traveled of the pedestrians at the experiment was 10.6 meters with standard deviation of 0.89 meters. The difference between the real average travel time and the simulation was 3.1% and for the average distance traveled was 1.8%.

I_{max} value variability has influence on the route distances and travel time. As I_{max} increases the route distance tends to decrease. However, for higher values of I_{max} the travel time tends to be extremely higher due to excessive congestion on shorter routes. Figure 8 shown the variability of travel times and distance for different values of I_{max}.

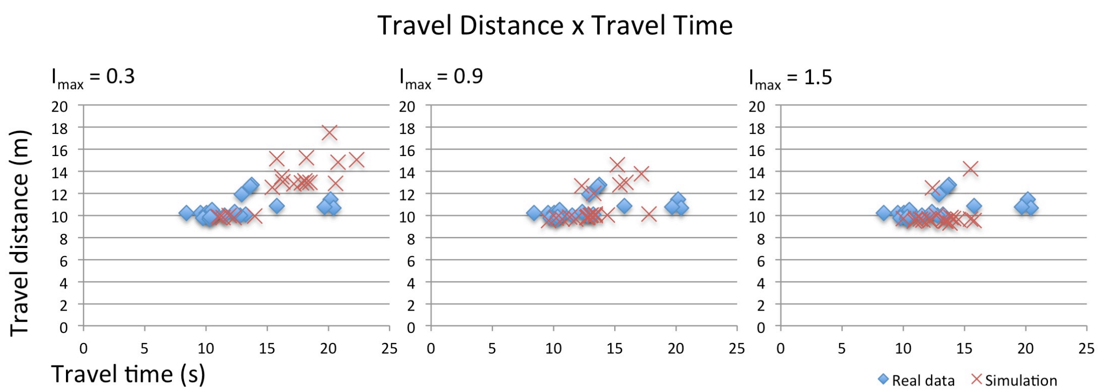


Figure 8 – Traveled distances

The network in this experiment has four minimal routes {8-7-5-3-1}, {8-6-5-3-1}, {8-6-4-3-1}, {8-6-4-2-1}. A minimal route choice model would assign pedestrians to any of these routes. However, in real circumstances pedestrians do not chose routes based only on distances. Pedestrians tend to avoid congested routes. This behavior was evident in experiment, as showed in color map (Figure 5). Through adjustment of I_{max}, calibrated model was able to realistically represent pedestrians' decisions to avoid links congested by fixed route pedestrians. These results show impedance equations ability to model route choice under congested conditions.

6.0. Validation

Model validation is needed to assess model representativeness in different situations. Validation data were collected on the same network previously presented. The configuration of fixed route pedestrians and free route pedestrians remains, but now the number of pedestrians on fixed group was reduced to a half, remaining only 10 pedestrians. Reducing the number of pedestrians on fixed route reduce the flow generating gaps between pedestrians. Free route pedestrians are now expected to be more spread out on network comparing to previous experiment.

Figure 9 shows two datasets collected from video analysis (Experiment run 1 and 2). For each run, volunteer's group performing free route pedestrians was completely changed. The heat maps were generated considering the traversed route for 20 free route pedestrians.

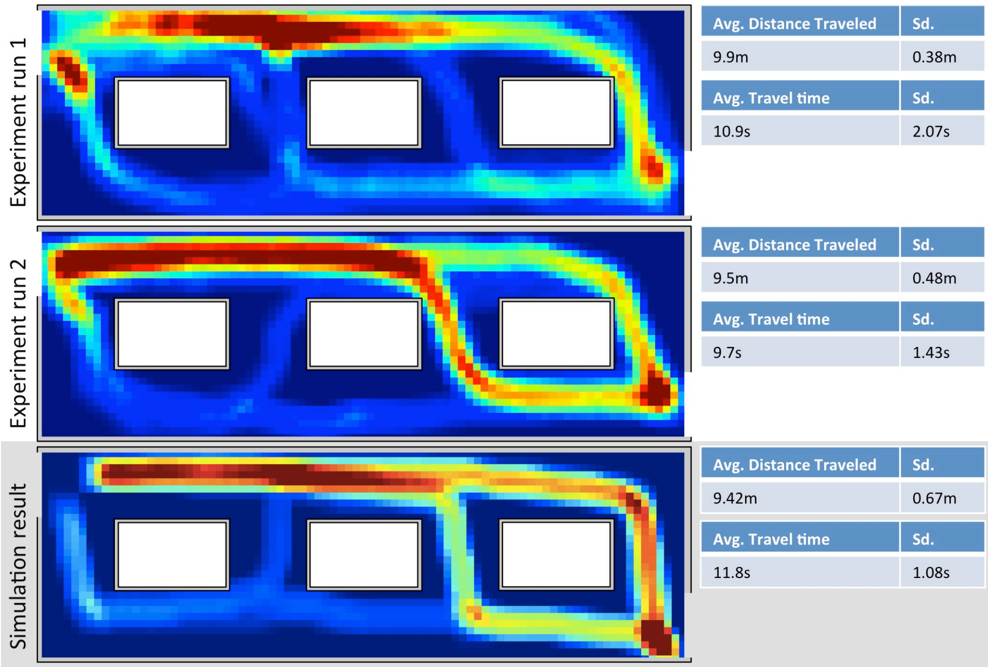


Figure 9 – Validation data

As expected, free route pedestrians are now far most overspread in network compared with previous experiment. The simulation result (Figure 9) was run for this new scenery with previously calibrated value of Imax. (Imax = 0.9). Simulation heat map is quite similar to data collected. The effect of weaker flow of fixed route pedestrians can be observed on both collected and simulated heat maps. Free route pedestrians are still avoiding the fixed route pedestrians, but now, in a more subtly way. In the previous experiment, almost all free route pedestrians diverted from the fixed route immediately upon entering the scenario, choosing the link between the corners {8 - 7}. This avoiding behavior is now split into other links. Higher congested links are now between corners {5 - 3 - 1}. These similarities between collected and simulated data show the model could be used to represent real pedestrians' behavior.

6. CONCLUSIONS

Route choice is a complex process to model since most route selection strategies are based on subconscious decisions. Perception of distance and directness are most common reasons for choosing a particular route, however, other factors may also play an important role in this decision, such as density of people and people walking in the opposite direction. This model assumes cost of a route as a function of route length and impedance generated by other pedestrians. The impedance generated by friction between pedestrians is generated even before physical contact, representing the psychological tendency to avoid passing close to individuals with high relative velocity. This modeling approach provides a sound representation of pedestrian route choice dynamics. Simulations results were calibrated with real data and indicate this model provides a promising approach for real case applications. Balance between impedance and distance could be easily calibrated with a single parameter. The model approach seamlessly incorporates pedestrians social force model into route choice decision process, and emerges as a promising approach for pedestrian route choice simulation.

7. REFERENCES

(1) Helbing, D., L. Buzna, A. Johansson and T. Werner. 2005. Self-Organized Pedestrian Crowd Dynamics. Transportation Science, 39 (1), 2005. 1- 24.
(2) Helbing, D., I. Farkas and T. Vicsek. 2000. Simulating dynamical features of escape panic. Nature 407, 487-490.
(3) Sumpter, D. 2006. The principles of collective animal behaviour. Phil. Trans. R. Soc. B 361, 5–22.
(4) Helbing, D. 1991. A mathematical model for the behavior of pedestrians. Behavioral Sci. 36 298–310.
(5) Helbing, D. 1997. Verkehrsdynamik [Traffic Dynamics]. Springer, Berlin, Germany.
(6) Helbing, D., P. Molnár, I. Farkas and K. Bolay. 2001. Self-organizing pedestrian movement. Environ. Planning B 28 361–383.
(7) Helbing, D. and P. Molnár. 1997. Self-organization phenomena in pedestrian crowds. F. Schweitzer, ed. Self-Organization of Complex Structures: From Individual to Collective Dynamics. Gordon and Breach, London, U.K., 569–577.
(8) Isobe, M., D. Helbing and T. Nagatani. 2004. Many-particle simulation of the evacuation process from a room without visibility. Physical Rev. E 69 066132.
(9) Teknomo, K. 2008. Modeling mobile traffic agents on network simulation. Proceedings of the 16th Annual Conference of Transportation Science Society of the Philippines (TSSP), Manila.
(10) Hill, M.R. 1982. Spatial Structure and Decision-Making of Pedestrian Route Selection Throught An Urban Envorironment, Ph.D Thesis, University Miocrofilms International.
(11) Senevarante, P.N., J. Morall. 1986. Analysis of factores affecting the choice of route of pedestrians. Transportation Planning and Technology 10, 147-159.
(12) Kirik, E. S., Yurgel'yan, T. B. and Krouglov, D. V. 2009. The shortest time and/or the shortest route strategies in a CA FF pedestrian dynamics model. Journal of Siberian Federal University. Mathematics & Physics, 2, 271–278.
(13) Dressler, D., M. Groß, J. Kappmeier, T. Kelter, J. Kulbatzki, D. Plu¨mpe, G. Schlechter, M. Schmidt, M. Skutella, and S. Temme. 2010. On the use of network flow techniques for assigning evacuees to exits. Procedia Engineering, 3, 205–215.
(14) Lämmel, G., M. Plaue. 2012. Getting out of the way: Collision avoiding pedestrian models compared to the real world. Pedestrian and Evacuation Dynamics.
(15) Papadimitriou, E. 2012. Theory and models of pedestrian crossing behaviour along urban trips. Transportation Research Part F: Traffic Psychology and Behaviour, 15, 75-94.
(16) Kretz, T., A. GROßE, S. Hengst, L. Kautzsch, A. Pohlmann, P. Vortisch. 2011. Quickest Routes in Simulations of Pedestrians. Advances in Complex Systems 14.05, 733-759.
(17) Patil, S. J. Berg, S. Curtis, M. Lin, D. Manocha. 2010. Directing crowd simulations using navigation fields, IEEE Transactions on Visualization and Computer Graphics, 244-254.
(18) Treuille, A., S. Cooper, Z. Popović. 2006. Continuum crowds. ACM Transactions on Graphics (TOG), 25. No. 3. ACM, 2006.
(19) Teknomo, K., D. Bauer and T. Matyus. 2008. Pedestrian Route Choice Self-Organization. Proceeding of the 3rd International Symposium of Simulation in Transportation, Gold Coast, Australia.

(20) Charreyron, S., Jackson, S., & Miranda-Moreno, L. F. 2013. Toward a flexible system for pedestrian data collection with a Microsoft Kinect motion-sensing device. Transportation Research Record: Journal of the Transportation Research Board, 80-89.

(21) Moussaïd, M., Helbing, D., Garnier, S., Johansson, A., Combe, M., and Theraulaz, G. 2009. Experimental study of the behavioural mechanisms underlying self-organization in human crowds. Proceedings of the Royal Society B: Biological Sciences, rspb-2009.

(22) Hoogendoorn, S. P., Daamen, W., & Bovy, P. H. 2003. Extracting microscopic pedestrian characteristics from video data. In Transportation Research Board 2003 Annual Meeting.

(23) Ming, T. and Hongfei Jia. 2011. An approach for calibration and validation of the social force pedestrian model. Transportation, Mechanical, and Electrical Engineering (TMEE), 2011 International Conference on. IEEE.

(24) Wang, T., Wu, J., Zheng, P. and McDonald, M. 2010. Study of pedestrians' gap acceptance behavior when they jaywalk outside crossing facilities. Intelligent Transportation Systems (ITSC), 2010 13th International IEEE Conference on. IEEE.

(25) Schönauer, R., Stubenschrott, M., Schrom-Feiertag, H., and Menšik, K. 2012. Social and Spatial Behaviour in Shared Spaces. Proceedings Real Corp 2012, 759–767.

(26) Werberich, B., Pretto, C. and Cybis, H. 2014. Pedestrian route choice model based on friction forces. Simulation: 0037549714547295.

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

(28) Gaud, N., S. Galland, F. Gechter, V. Hilaire, A. Koukam. 2008. Holonic multilevel simulation of complex systems: Application to real-time pedestrians simulation in virtual urban environment. Simulation Modelling Practice and Theory, 16, 1659–1676.

(29) Pretto, C. O., A. C. Jacobsen, H.B.B. Cybis. 2011. A multi-layer simulation model for vehicle and pedestrian. 90th Anual Meeting Transportation Research Board, 1, 1-15, Washington.

(30) Dijkstra, E. 1959. W.A note on two problems in connexion with graphs. Numerische Mathematik, 1, 269–271.

(31) Werberich, B., Pretto, C., and Cybis, H. 2014. Pedestrians' Route Choice Based On Friction Forces Assuming Partial And Full Environment Knowledge. Transportation Research Board 93rd Annual Meeting.

(32) Tracker. Video analysis and modeling tool. Retrieved from https://www.cabrillo.edu/~dbrown/tracker/

(33) Johansson, A., Helbing, D., and Shukla, P. 2007. Specification of the social force pedestrian model by evolutionary adjustment to video tracking data. Advances in complex systems, 271-288.

5. FOURTH PAPER

"Following a route: a force field generated from a sequence of points on the plane"

Following a route: a force field generated from a sequence of points on the plane

ABSTRACT

Route choice is one of the most important activities performed by pedestrians. Graph based algorithms consider that a route is defined as a sequence of nodes. To follow a route a pedestrian must move to each of the nodes on the route sequence. This paper proposes a method to smooth pedestrians' routes and guide pedestrians by generating a vector field.

1. Introduction

Route choice is one of the most import pedestrian activities. Many simulation models are concerned with the pedestrian rout choice [1][2][3][4][5]. Among the criteria for a route choice, simulation models frequently address distance and jams [2][3][5]. Even with a defined route pedestrians may find obstacles that require some deviations from the original route. Simulated pedestrians should have flexibility to follow a route. Minor deviations from the original route don't require route recalculation, which can be computationally expansive.

Route choice algorithms based on graphs, as Djikstra [6] and A* [7], find the lowest cost route between two graph nodes. In this way, a route is defined as a sequence of nodes geographically placed on the environment. To follow a route a pedestrian must move for each of the nodes on the route sequence. Reaching one of the nodes, the pedestrian change its direction to the next node. The point-to-point displacement results in non-realistic movements, with sudden changes in the direction of motion, mostly with pedestrians facing many obstacles.

The Social Forces Model [8] describes the pedestrian displacement as a sum of many forces exerted on the pedestrian. One of these forces is defined as the desired direction of motion ($\vec{e}$). Following a route, a pedestrian directs its vector $\vec{e}$ to the next point on the route sequence. This paper presents a method to smoothly adjust the vector $\vec{e}$ for a simulated pedestrian to ensure smooth and realistic movements. Proposed method generates a vector field to give the pedestrian a vector $\vec{e}$ anywhere on a plane, even with deviations from the original route.

2. Route Calculation

As previously mentioned, a route is generated from a graph. Figure 1 shows six steps (A to F) regarding route definition and smoothing. On Step 'A' is presented the graph. Green node represent the origin, red node represent the destination. Step 'B' shows the chosen route in orange. Collinear nodes must be removed from the route (Step 'C'), only nodes presenting changing direction are kept.

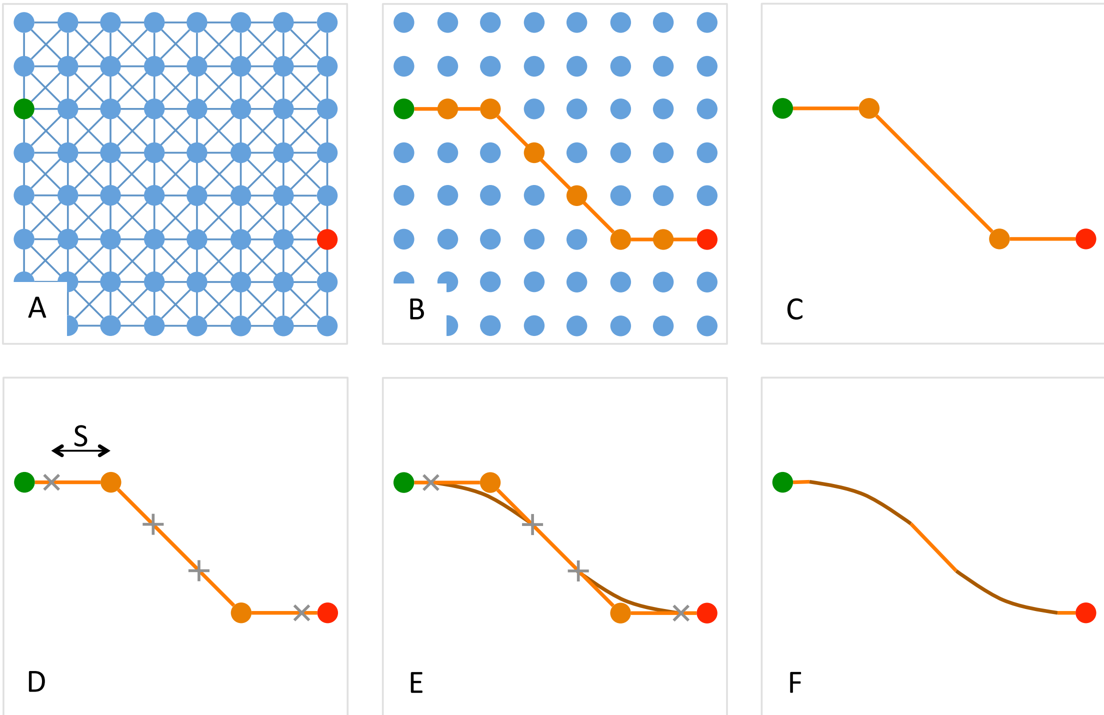


Figure 1 – Route definition and Smoothing

The route smoothing process is performed from step 'D' onwards. The route trace will be represented as a set of quadratic Bézier curves [9]. Three control points define a quadratic Bézier curve. All the orange nodes kept on the route, after removing the collinear nodes (Figure 1 - Step 'C') will represent a central control point of a Bézier curve. The other two needed control points are added for each curve, represented by grey 'X'.

The distance between the control points, S, is a settable parameter. The distance S configuration must consider the scenario layout. Increasing S makes the pedestrian trajectory smoother. Scenarios with narrow aisles have limitations regarding smoothing, comparing with large spaces.

Step ‘E’ (Figure 1) shows the Bézier curves definitions. Step ‘F’ shows the final route trace, on which the pedestrian will be guided.

3. Following The Route

To guide a pedestrian walking over the defined route trace it is necessary to provide an orientation vector to the pedestrian ($\vec{e}$). It is possible to calculate a vector $\vec{e}$ anywhere in a plane, generating an vector field. The desired direction of motion of a pedestrian, represented by the vector $\vec{e}$, can be calculated as a sum of two vectors: vector $\vec{O}$, orthogonal to the Bézier curve and vector $\vec{T}$, tangent to the curve.

Figure 2 shows variables involved on the vector $\vec{e}$ calculation. On Figure 2 the green circle (point M) represent a pedestrian. The pedestrian aims to follow the route defined by the Bézier curve B(t). The vector $\vec{O}$ keeps the pedestrian closer to the route trace and the vector $\vec{T}$ directs the pedestrian along the route. Vector $\vec{e}$ is the result of the sum of vectors $\vec{O}$ and $\vec{T}$.

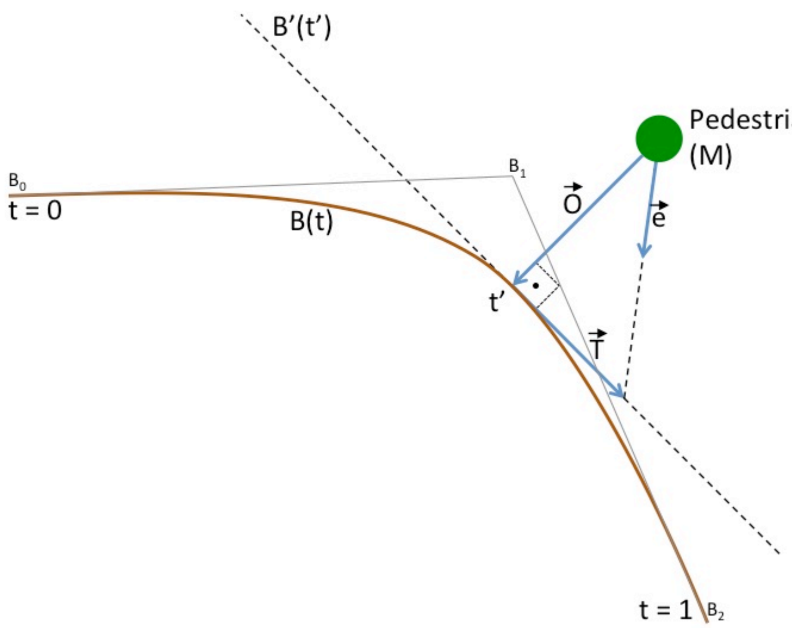


Figure 2 – Vector $\vec{e}$ definition

The calculation of vectors $\vec{O}$ and $\vec{T}$ is a complex problem considering higher order Bézier curves. However, for quadratic Bézier curves it is possible to calculate the vectors analytically.

Equation 1 defines a quadratic Bézier curve [9]:

$$B(t) = (1-t)^2 B_0 + 2t(1-t)B_1 + t^2 B_2, \qquad t \, \varepsilon \, [0,1]$$

Where: B_0, B_1 and B_2 are the control points of the curve, t is the independent variable, varying in the range [0, 1].

The vector $\vec{O}$ is the shortest possible vector starting on point M and ending over the curve B(t). Vector $\vec{O}$ is orthogonal to the curve B(t). To calculate the tangent line at a certain point over a curve it is necessary to calculate the derived function.

The derivative function of a quadratic Bézier curve is defined at Equation 2:

$$B'(t) = -2(1-t)B_0 + 2(1-2t)B_1 + 2tB_2$$

In a simplified way:

$$B'(t) = 2(A + Bt)$$

Where: $A = (B_1 - B_0) \; and \; B = (B_2 - B_1 - A)$

With Equations 1 and 2 it is possible to calculate the value of t where the distance between B(t) and M is shortest possible. This value of t is defined as t'. Vector $\vec{O}$ is orthogonal to B(t'). To find t' it is possible to define vector $\vec{O}$ as $\vec{O}$ = MB(t'). Knowing that the dot product between two orthogonal vectors is equal to zero: MB(t') . B'(t') = 0.

The dot product MB(t') . B'(t') is shown on Equation 3:

$$(M - (1-t)^2 B_0 + 2t\,(1-t)B_1 + t^2 B_2) \, . \, (A + Bt) = 0$$

In a simplified way:

$$at^3 + bt^2 + ct + d = 0$$

Where: $a = B^2, b = 3AB, c = 2A^2 + M'B, d = M'A, (M' = B_0 - M)$

The value of t' can be found solving the simplified Equation 3. It is possible to solve a cubic polynomial equation analytically using the Cardano's method.

In this model a route is defined as a set of quadratic Bézier curves. In this way, to evaluate vector $\vec{\mathrm{e}}$ for a pedestrian in some point on plane it is necessary to choose only one Bézier curve on the set. To find the closest curve to the pedestrian the vector $\vec{\mathrm{O}}$ must be calculated for all the Bézier curves on the set. The curve with the smaller module value for vector $\vec{\mathrm{O}}$ is the closest one to the pedestrian.

$\vec{\mathrm{e}}$ is the resultant vector of the sum of $\vec{\mathrm{O}}$ and $\vec{\mathrm{T}}$. Vector $\vec{\mathrm{O}}$ exerts grater influence on points that are distant from the route. For distant points, vector $\vec{\mathrm{O}}$ has large module values. In this way, when a pedestrian is distant from the route, there will be a strong tendency to bring the pedestrian back to walk closer to the route. Vector $\vec{\mathrm{T}}$ has the same direction of vector B'(t'), however, vector $\vec{\mathrm{T}}$ has constant module value. The vector $\vec{\mathrm{T}}$ module is a settable parameter. Higher values for the module of $\vec{\mathrm{T}}$ make pedestrians less prone to walk closer to the route and more concerned following the route direction. Vector $\vec{\mathrm{e}}$ is the sum of the vectors $\vec{\mathrm{O}}$ and $\vec{\mathrm{T}}$, however, after the sum, vector $\vec{\mathrm{e}}$ is normalized and used as a unit vector. Its function is to provide only direction, regardless of its modulus.

4. Results

Figure 3 shows the vectors $\vec{O}$ (green) and $\vec{T}$ (blue) for a given route (red lines). The route in red is defined by four points on plane, resulting in three lines segments with sudden changes in direction. Vectors $\vec{O}$ and $\vec{T}$ were calculated for many points on the plane according to presented equations. It is possible to observe that vectors $\vec{O}$ are orthogonal to smoothed route, connecting each point on the plane with the route. Vectors $\vec{T}$ are parallel to the route and have constant module.

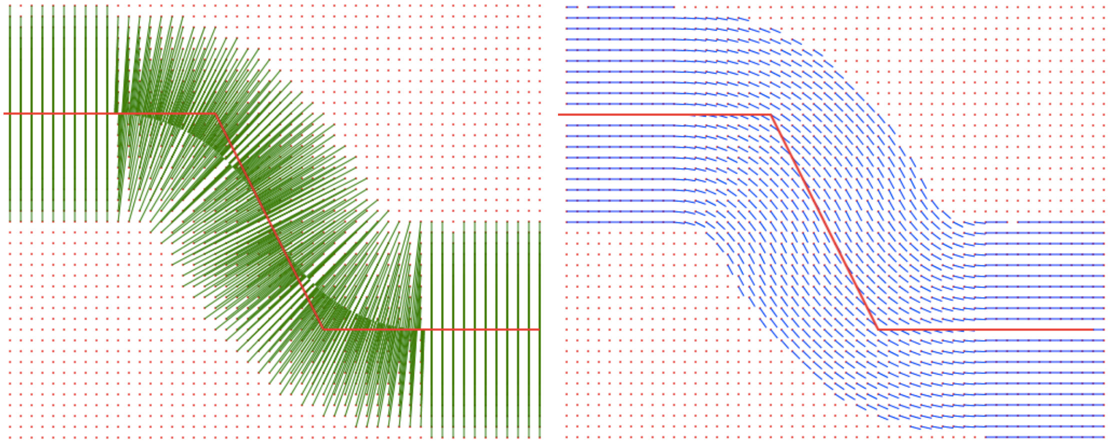


Figure 3 – Vectors $\vec{O}$ e $\vec{T}$

Figure 4 shows the final result for the proposed method, the vector field to provide the desired direction of motion ($\vec{e}$) to the pedestrian. It is possible to observe that for closer points the vector $\vec{e}$ presents minor changes in its direction, guiding the pedestrian smoothly.

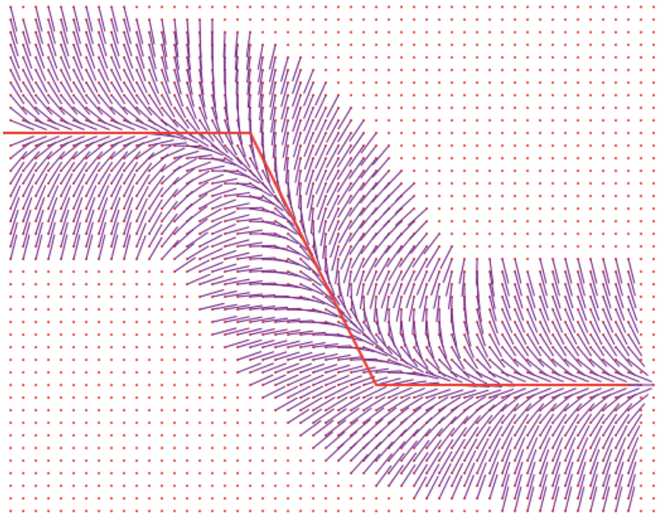


Figure 4 – Vector field – Desired direction of motion

For points on the route, vector $\vec{e}$ guides the pedestrian to walk in a tangent direction to the route. Vectors away from the route are not shown. When a pedestrian is too far away from the original route he must recalculate the route.

Figure 5 shows the effect of the distance S (Figure 1) between the Bézier control points on the generated vector field. On the first image of Figure 5 S has a small value. In this configuration a pedestrian is guided closer to the original straight lines, which generate the route. On the second image (Figure 5) S has a higher value.

In this configuration a pedestrian is guided more smoothly but distant to the original straight lines.

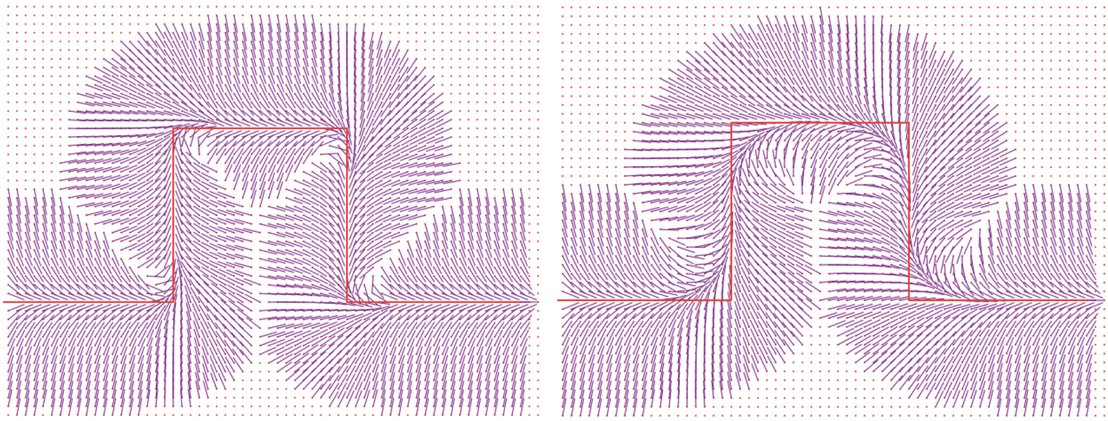


Figure 5 – The effect of the distance between the Bézier control points

Figure 6 shows the effect of the vector $\vec{T}$ module value on the vector field. The first image of Figure 6 was obtained with a small value for the $\vec{T}$ module. In this configuration, pedestrians' priority is to walk closer to the smoothed route. On the second image (Figure 6) it was set a higher value for vector $\vec{T}$ module. In this case, pedestrians walk towards the destination, even if away of the original route.

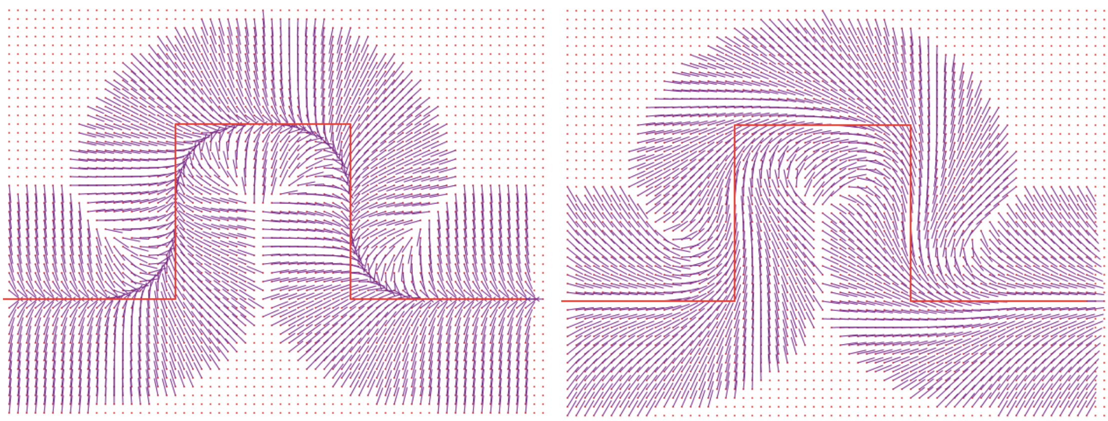


Figure 6 – The effect of the vector $\vec{T}$ module value

5. Conclusions

Presented method allows the generation of a vector field based on tradition methods for route choice based on graphs. Generated vector field provide the desired direction of motion for a pedestrian in any position on a plane. Proposed model has settable parameters that allow the adaptations on the vector field to particularities of the environment and the representation of different pedestrian profiles.

Traditional pedestrians simulation models can easily adopt the proposed method. This method is an interface between two classical layers on pedestrians' simulation: The route choice (Djikstra, A*) [6][7] and the sense and avoidance layer (Social Forces Model)[8].

Referencias

[1] Dressler, D., Groß, M., Kappmeier, J. P., Kelter, T., Kulbatzki, J., Plümpe, D., and Temme, S. (2010). On the use of network flow techniques for assigning evacuees to exits. Procedia Engineering, 3, 205-215.

[2] Kirik, E., Yurgel'yan, T. Y., and Krouglov, D. (2009). The shortest time and/or the shortest path strategies in a CA FF pedestrian dynamics model. arXiv preprint arXiv:0906.4265.

[3] Kretz, T., GROßE, A. N. D. R. E. E., Hengst, S., Kautzsch, L., Pohlmann, A., and Vortisch, P. (2011). Quickest paths in simulations of pedestrians. Advances in Complex Systems, 14(05), 733-759.

[4] Crociani, L., Invernizzi, A., and Vizzari, G. (2014). A hybrid agent architecture for enabling tactical level decisions in floor field approaches. Transportation Research Procedia, 2, 618-623.

[5] Hartmann, D., Mille, J., Pfaffinger, A., and Royer, C. (2012). Dynamic medium scale navigation using dynamic floor fields. In Pedestrian and Evacuation Dynamics 2012 (pp. 1237-1249). Springer International Publishing.

[6] Dijkstra, E. W. (1959). A note on two problems in connexion with graphs. Numerische mathematik, 1(1), 269-271.

[7] Hart, P. E., Nilsson, N. J., and Raphael, B. (1968). A formal basis for the heuristic determination of minimum cost paths. IEEE transactions on Systems Science and Cybernetics, 4(2), 100-107.

[8] Helbing, D., and Molnar, P. (1995). Social force model for pedestrian dynamics. Physical review E, 51(5), 4282.

[9] Bézier, P.: Mathematical and practical possibilities of UNISURF. In: R.E. Barnhill, R.F. Riesenfeld (eds.) Computer Aided Geometric Design, pp. 127–152. Academic Press, New York (1974)

6. FIFTH PAPER

"Pedestrians' Route Choice Model for Shopping Behavior" [20]

Pedestrians' Route Choice Model for Shopping Behavior

Bruno Rocha Werberich   Carlos Oliva Pretto   Helena Beatriz Bettella Cybis
Department of Production Engineer
Federal University of Rio Grande do Sul
Porto Alegre, Brazil
{bruno.rwe;cpretto}@gmail.com , helenabc@producao.ufrgs.br

Abstract

This paper presents an agent-based model to address the pedestrian route choice problem in shopping malls. Route choice in shopping malls may be defined by a number of causal factors. Shoppers may follow a pre-defined schedule, they may be influenced by other people walking, or may want to get a glimpse of a familiar shopping. The route choice process assumes that the cost of each route can be calculated as a function of three factors: route length, impedance generated by other pedestrians and attraction for areas of interest on the environment. The impedance generated by the friction between pedestrians is assumed to exist even before physical contact, due to the psychological tendency to avoid passing close to individuals with high relative velocity. Pedestrians seek minimal route length and minimal friction with other pedestrians. In order to represent shopping areas environments, a new factor is being considered in the calculation of the route cost: the attraction for areas of interest on the environment. Simulation results were compared to real data collected by video recording in a shopping mall.

1 Introduction

Modelling of pedestrian's behavior is a complex task and has been studied by different research areas. In order to represent motion of pedestrians more realistically, models are required to simulate several processes, including sense and avoidance of obstacles, interaction with other pedestrians and route choice. Agent-based abstraction has been widely used for pedestrian modeling, mainly due to its capacity to provide insights about system´s reactions from changes on entities proprieties, capturing information over space and time at a detailed level [Klügl and Bazzan 2012; Macal et al. 2006; Rossetti R. et. al. 2002]. Agent-based models represent agents' decision-making ability based on their profile and perception over the environment.

Agent-based pedestrians models require the aggregation of different levels of abstraction, that are modeled on different layers. The majority of pedestrian models present a multi-layer simulation approach [Gaud et al. 2008; Hoogendoorn et al. 2002] composed by, at least, two layers: a tactical and an operational layer.

The tactical layer chooses a path regarding an origin-destination pair and a route choice criteria such as minimum distance and/or travel times. The tactical model determines the desired pedestrian directions, which are used in the operational model [Pretto et al. 2011].

The operational model determines the low level microscopic movements of pedestrians. It is ruled by principles of pedestrians'sense and avoidance of obstacles. Most models reported in literature can be regarded as using force-based approaches [Helbing et al. 1991; Helbing et al. 1995]. In force-based models, agents evaluate forces exerted by infrastructure and by other agents. Helbing and Molnar (1995) presented a relevant work on force-based models in which they use Newtonian mechanics and a continuous space representation to model a long-range interaction. The concept behind this approach suggests that the motion of a pedestrian can be described by combination of several forces (including the repulsive forces from walls and other pedestrians). The social force model reproduces various emergent phenomena observed on pedestrian´dynamics.

The tactical model is responsible for route choice. Realistic route choice is a complex process because most route selection strategies are based on subconscious decisions. Most models presented in the literature are concerned only with the quickest or shortest route, like Kirik et. al. (2009), Dressler et. al. (2010) and Lämmel et. al. (2014). However, other factors play an important role in route choice behavior, such as: peoples' habits, number of crossings, pollution and noise levels, safety, shelter from poor weather conditions and other environment stimulations [Papadimitriou E., 2012]. Most relevant route choice models are concerned with pedestrians' evacuation. In Kretz et. al. (2011), for instance, pedestrians routes are chosen based on the minimal remaining travel time to destination. Kretz et. al. (2014) introduce a generic method for dynamic assignment used with microsimulation of pedestrian dynamics. In the paper, the routes mark the most relevant routing alternatives in any given walking geometry, reducing the infinitely many trajectories by which a pedestrian can move from origin to destination to a small set of routes. Crociani and Lämmel (2016) present a work with two major topics. In the first topic, a novel cellular automaton (CA) model is proposed, which describes the pedestrian movement by a set of simple rules, and the second topic describes how the CA can be integrated into an iterative learning cycle where the individual pedestrian can adapt travel plans based on experiences from previous iterations. Patil et. al. (2010) propose an interactive algorithm to direct and control crowd simulation. The model presented by Treuille et. al., (2006) unifies route planning and local collision avoidance by using a set of dynamic potential and velocity. Teknomo (2008) and Teknomo et al., (2008) described a self-organization route choice approach to model the dynamics of agents, such as pedestrians and cars on a simple network graph. The agents decide, when reaching a vertex, which edge to enter next. This decision is based on a set of rules regarding the agent's observation of the local environment. In order to represent complex networks, such as shopping areas and urban scenarios, agents need to represent more complex caracteristics and capabilities.

The literature presents several agent-based applications to simulate different pedestrians' behaviors and environments. The pedestrians' simulation in a commercial environment, such as shopping malls, is particularly complex since pedestrians are exposed to different stimulus and attractions [Wang, W. et. al. 2014]. Agent-based simulation is particularly valuable for these cases because environment stimulus exert distinct influences depending on the person profile. Dijkstra et al., (2013) provide a model for pedestrian activity simulations in shopping environments. This framework provides an activity agenda for pedestrian agents, guiding their shopping behavior in terms of destination and time spent in shopping areas. Pedestrian agents need to successively visit a set of stores and move over the network. The authors assumed that pedestrian agents' behavior is driven by a series of decision heuristics. Agents need to decide which stores to choose, in what order and which route to take, subject to time and environment constraints.

Route choice in shopping malls may be defined by a number of causal factors. Shoppers may follow a pre-defined schedule, they may be influenced by other people walking, or may want to get a glimpse of a familiar shopping.

Shopping agents, as described in the literature [Borgers, A., and Timmermans, H., 1986; Ali, W. and Moulin, B., 2006] usually decide (i) in which stores to stop, (ii) in what order and (iii) which route to take. In practice, however, shopping mall users´ behaviour is a combination of planned and unplanned decisions. Planned decisions can defined by a set of origin-destination pairs. Unplanned decisions may be resultant from eventual impulses or the attraction exerted by shopping windows.

This paper presents an agent-based route choice model to represents pedestrians' in a shopping mall environment. The pedestrian model allows the representation of shopping users capable to perform either planned and unplanned behaviour, depending on the agent´s profile. Simulation results were compared to real data collected by video recording in a shopping mall.

2 The Model

An agent-based model is proposed to address pedestrian route choice problem. Agent-based models represent agents' decision-making ability based on agents' characteristics profile and perception over the environment. In the proposed model, pedestrians are agents able to choose and recalculate routes. Pedestrians are not assigned to predetermined routes.

In this model, a route is a set of coordinates followed by a pedestrian from origin to destination. Route choice process comprises three factors for calculation: (i) distance, (ii) interaction with other pedestrians (avoiding jams) and (iii) attraction for areas of interest on the environment (in this specific case: shop windows).

The framework adopted to describe pedestrian behavior in this model (Figure 1) presents a three-layer structure, each layer representing:

(i) Demand for travel - set of origin and destination. Each origin-destination pair is associated to a number of trips and a pedestrian generation rate. Origins and destinations are associated with nodes on the environment layer.

(ii) Simulation environment structure -.The environment is described as a continuous space and is composed by geometric entities, such as rooms, doors, and other obstacles. The environment entities are linked by a graph-based structure providing a route to all entities. In this model, nodes are defined by a set of coordinates (x, y). Nodes also contain properties defining local features of the environment.

(iii) Pedestrians movement, sense and avoidance of obstacles: set of equations and agents behavior rules. The social force model (1) describes pedestrian walking behavior regarding agents' low-level motion, collision avoidance and velocity adaptation. Pedestrians freely walk on the modeling environment seeking the next graph node of the designated route. Pedestrians' movements are ruled by the sense and avoidance model and are not restricted to a strict set of links.

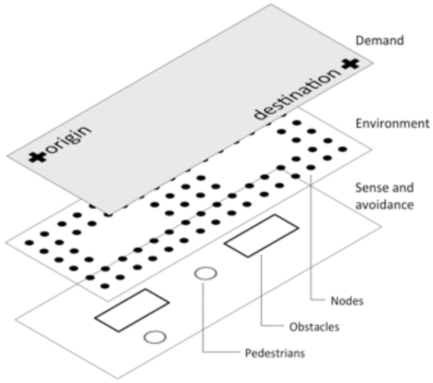


Figure 1 - Layers

2.1 The Route Choice Process

The presented route choice process is derivate from model established by Werberich et. al. (2014). Werberich et. al. propose that the cost of each route can be calculated as a function of two factors: route length and the impedance generated by other pedestrians. The impedance generated by the friction between pedestrians is assumed to exist even before physical contact, due to the psychological tendency to avoid passing close to individuals with high relative velocity [Helbing D. et al., 2000]. Pedestrians seek minimal route length and minimal friction with other pedestrians. In this model, a new factor is being considered in route cost calculation: attraction for areas of interest on the environment.

The total route cost is the sum of all link costs. Dijkstra algorithm [Dijkstra E., 1959] is adopted to generate valid routes for any origin/destination pair. Figure 2 describes the cost calculation for a link.

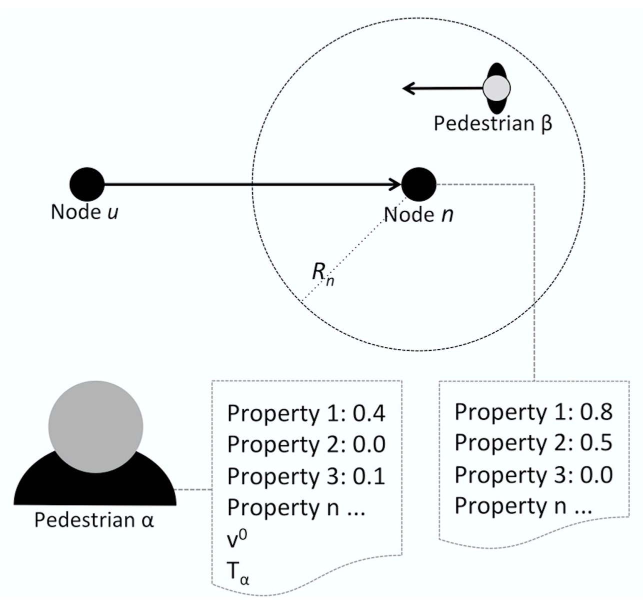


Figure 2 – Pedestrian's profile and node attraction

Figure 2 presents the elements involved in the route choice process. The cost estimation for a Pedestrian α to walk from node u to n involves three factors: (i) the distance between nodes ($\|\vec{r_n} - \vec{r_u}\|$), (ii) the impedance perceived by the pedestrian α exerted by other pedestrians (I_α) and (iii) the environment attraction perceived by pedestrian α for the node n (A_α^n).

Impedance exerted by the pedestrians in the simulation is calculated by simple vectors operations. Subtracting the desired velocity of pedestrian α from the velocity of pedestrians closer to node n (pedestrians β) it is possible to estimate I_α (equation 1).

$$I_\alpha = \sum_\beta \left| \vec{v_\beta} - \left(\frac{\vec{r_n} - \vec{r_u}}{\|\vec{r_n} - \vec{r_u}\|} \right) * v_\alpha^0 \right| \quad (1)$$

where:
$\vec{v_\beta}$ = Pedestrian's β current velocity;
$\vec{r_n}$ = Node's n vector position;
$\vec{r_u}$ = Node's u vector position ;
v_α^0= Pedestrian's α desired speed.

The calculation of I_α considers a neighborhood area around the node n, defined by the radius R_n. All pedestrians inside the neighborhood area, at the instant of the route choice, are nominated pedestrians β. I_α is the sum of the friction forces exerted by each pedestrian β over the desired velocity of the pedestrian α.

As mentioned above, the graph nodes contain properties that classify local features of the environment. Node properties define the environment characteristics. For example, properties can be defined as female clothes store, male clothes store, electronics store, shoe store, etc. Nodes are defined by a set of values for all simulated properties. Higher properties values mean the node is closer of the related feature. Properties can assume values in the range [0 – 1].

The attraction exerted by these nodes properties on pedestrians vary dependeing on pedestrians profiles. Pedestrians' profiles also present a set of values for all simulated environment properties, that represent their attraction for these features. For example, male pedestrians probably have higher values for a property relating to a male clothes store. These properties also assume values in the range [0 – 1].

The attraction of node n, perceived by pedestrian α (A_α^n), is calculated as a weighted average (Equation 2):

$$A_\alpha^n = \frac{\sum_{i=0}^{p} P_i^\alpha * N_i^n}{\sum_{i=0}^{p} N_i^n} \quad (2)$$

where:

p = total number of properties;
P_i^{α} = pedestrian α property i value;
N_i^n = node n property i value.

The total estimated cost for pedestrian α to walk from node u to n ($W_{\alpha}^{u,n}$), is a balance between distance, impedance and attractiveness, as described in Equation 3:

$$W_{\alpha}^{u,n} = \|\vec{r}_n - \vec{r}_u\|. (1 + I_{\alpha} / I_{max} + (1 - A_{\alpha}^n)) \quad (3)$$

where:
I_{max} = settable parameter that adjusts the balance between distance and impedance. Further description of this parameter can be obtained in Werberich et al. (2014).

Elected routes minimize the total cost W_{α}. Equation 3 ensures pedestrians are attracted to areas of interest considering their profile. Pedestrians also avoid congested areas and passing close to other pedestrians with high relative velocity.

2.2 Pedestrian Stopping Behavior

It is expected that pedestrians walking on shopping environment, when attracted by an environmental stimulus, may stop for a while. For example, pedestrians attracted by a shop window frequently stop walking when they get closer to this interest point. This model simulates pedestrians route choice process subjected to attraction by interest areas, tipical of shopping environments.

To simulate pedestrians' stopping behavior the model introduces the concept of hotspots. Hotspots are defined by a location on the environment (x and y coordinates) and a neighborhood area (radius R). Hotspots have the same environment properties as graph nodes. When a pedestrian reaches the neighborhood area of a hotspot, he decides whether to stop or not. This decision process considers the pedestrian profile and the hotspot properties. Pedestrian profile includes a value denoting the tendency to stop on a hotspot (T_{α}). Higher values of T_{α} means the pedestrian have higher tendency to stop on hotspots. T_{α} values also respect the range [0–1]. Equation 4 defines the probability of a pedestrian α stopping on a hotspot q (S_{α}^q).

$$S_{\alpha}^{q} = \frac{\sum_{i=0}^{p}(P_i^{\alpha} * H_i^{q})}{\sum_{i=0}^{p} H_i^{q}} * T_{\alpha} \quad (4)$$

where:
p = total number of properties;
P_i^{α} = pedestrian α property i value;
H_i^n = hotspot q property i value;
T_{α} = pedestrian α tendency to stop on a hotspot.

If a pedestrian decides to stop on a hotspot neighborhood, the hotspot coordinates become his new destination for the stopping period. The balance between the pedestrian desired speed vector (v_{α}^{0}) and the forces exerted by the hotspot walls, keep the pedestrian standing in the neighborhood area. During this period, the interaction between pedestrians is maintained, allowing a realistic representation of pedestrians behavior at window shops. When a pedestrian stopping time has expired, a new route is recalculated to the final the destination.

The time a pedestrian stops at a hotspot may has variable assumptions. In this formulation, pedestrians stopping time is assumed to be fixed, equal to 20 seconds. Assumptions about stopping times can be discussed in more detail. An important work regarding time spent at store windows was developed by Dijkstra J. et. al. (2014). In this paper, authors describe the time spent in a store based on pedestrians profile and store segment.

Figure 3 presents a flowchart of the agent's internal process.

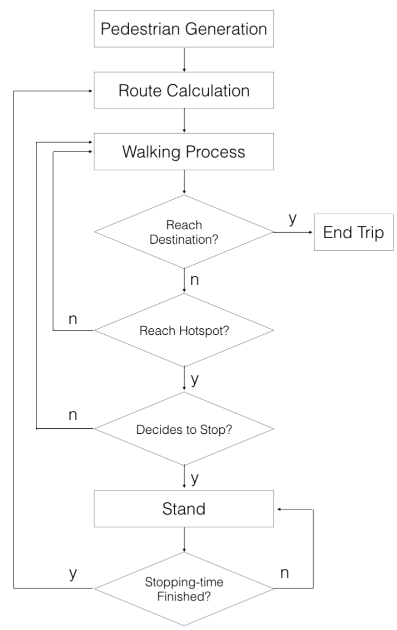


Figure 3 - Agent's internal process

As presented in this flowchart, a pedestrian only performs a route recalculation procedure after stopping at a hotspot. A Social Force-based route choice process considers the interaction with other pedestrians, which provides a dynamic behavior. However, if necessary, when simulating complex scenarios, the model structure allows the introduction of route recalculation areas. When simulating small scenarios, where the decision at the beginning of the trip was based on a good assessment of the way forward for all simulation timeframe, route recalculation may not be necessary.

3 Collected Data

Video data were collected in a shopping mall of Porto Alegre, Brazil. The camera collected images from a hall that connects the two main corridors of the first floor. Figure 4 presents an image of the studied area and the collected pedestrian routes.

The software *Tracker* was used to collect pedestrians' data in a semi-automatic process. The collected data is composed by a set of coordenates (*x and y*) over 1 minute of video for each pedestrian.

In order to simplify the data analysis, the enviroment was segmented in cells. A color map representing the cumulative occupation of each cell is shown at figure 5, segmented by gender.

Figure 4 – The Mall

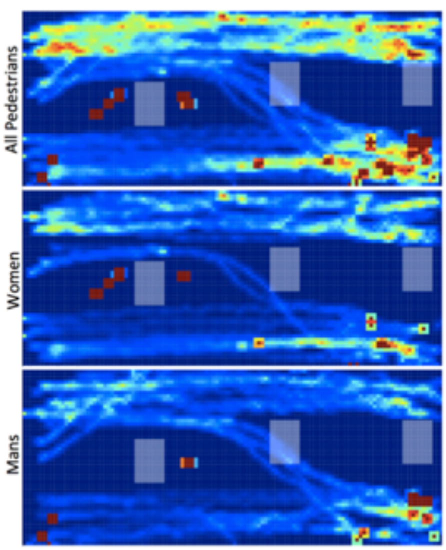


Figure 5 –Collected data

Data analysis allows the identification of three stores with higher pedestrian attraction . Table 1 shows the number of pedestrians, men (M) and women (W), that were attracted and stopped closer to these areas.

Table 1 – Stopped pedestrians

Store	M	W
jewelry	1	5
toy store	3	2
shoes store	2	3

4 Simulation

The proposed model has the potential to represent several properties regarding agents' profile and environment characteristics. In order to simplify the simulation, only two properties were considered in this experiment: Male Store Attraction (MSA) and Female Store Attraction (FSA). These two properties were applied to:

i. Scenario elements: hotspots and graph nodes (MSA_s and FSA_s);
ii. Agents (MSA_a and FSA_a).

The experiment was developed to identify the influence of MSAa and FSA_a in the number of pedestrians that are attracted to hotspots. The MSA_a and FSA_a were calibrated based on collected data.

The model was implemented using c# programming language (simulation engine) and Windows Presentation Foundation for the graphical interface.

4.1 Simulation Scenario

Figure 6 shows the simulation scenario built to represent the observed environment. Green areas (h1, h2, h3) are the hotspots. The hotspots correspond to stores where mall users used to stop on the real site. Dots are the graph nodes. Rectangles represent mall kiosks.

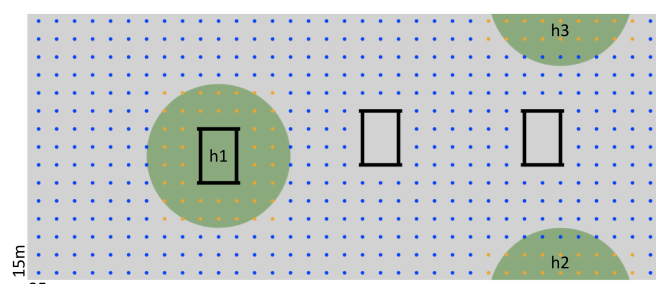


Figure 6 – Simulation scenario

Table 2 shows the values for MSA_s and FSA_s considered for the hotspots and its surrounding yellow graph nodes. Blue graph nodes (Figure 6) exert no attraction over the agent, the value for both MSA_s and FSA_s are zero. The MSA_s and FSA_s values were assumed to be constants. The MSA_s and FSA_s definition can be enhanced by considering effects of various design and management attributes. An example of the evaluation of consumers attraction can be found in Oppewal, H., and Timmermans, H. (1999). The authors estimated a stated preference model from responses to descriptions of an hypothetical shopping centers considering attributes such as: area for pedestrians, window displays, street layout, and street activities.

Table 2 – Hotspots configuration

hotspot	role	MSA_s	FSA_s
h1	jewelry	0.2	0.5
h2	toy store	0.8	0.6
h3	shoes store	0.8	0.6

4.2 Calibration

The calibration process aimed to calibrate the agents' profile (MSA_a and FSA_a) in order to reproduce the number of stopped pedestrians at each hotspot. For this purpose, four groups of simulations were run (s1, s2, s3, s4). For each simulation group, 50 simulations were performed. Two agents classes were implemented: male agents (MA) and female agents (FA). By definition, male agents have $FSA_a = 0$ and female agents have $MSA_a = 0$. Table 3 shows the configuration profiles defined for each simulation group.

Table 3 – Agents profile configuration

simulation group	MA	FA
s1	$MSA_a = 0.1$	$FSA_a = 0.1$
s2	$MSA_a = 0.5$	$FSA_a = 0.5$
s3	$MSA_a = 0.7$	$FSA_a = 0.7$
s4	$MSA_a = 0.9$	$FSA_a = 0.9$

The only variables in simulations were MSA_a and FSA_a. The scenario configuration was kept constant. Agents' tendency to stop (T_α) was set to 0.7. According to observed data, each simulation run comprised 80 agents, 40% MA and 60% FA. Pedestrians are generated with a fixed rate over time, with 40% of change to be male and 60% of change to be female. Figure 7 shows a simulation screenshot, MA are green circles and FA are red circles. A simulation video is availiable at: ***https://youtu.be/10OUgNMaoNA***.

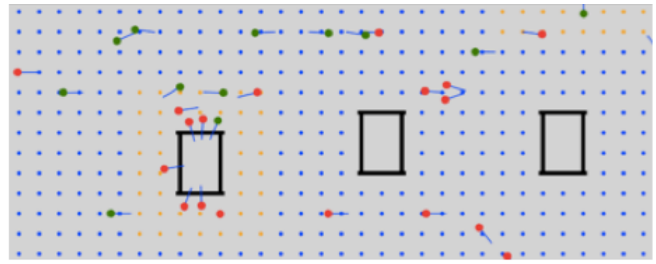


Figure 7 – Simulation screenshot

Figure 8 shows a color map of the results for all simulation groups (s1, s2, s3, s4), and the average number of agents stopping at each hotspot (h1, h2, h3) over 50 simulation runs.

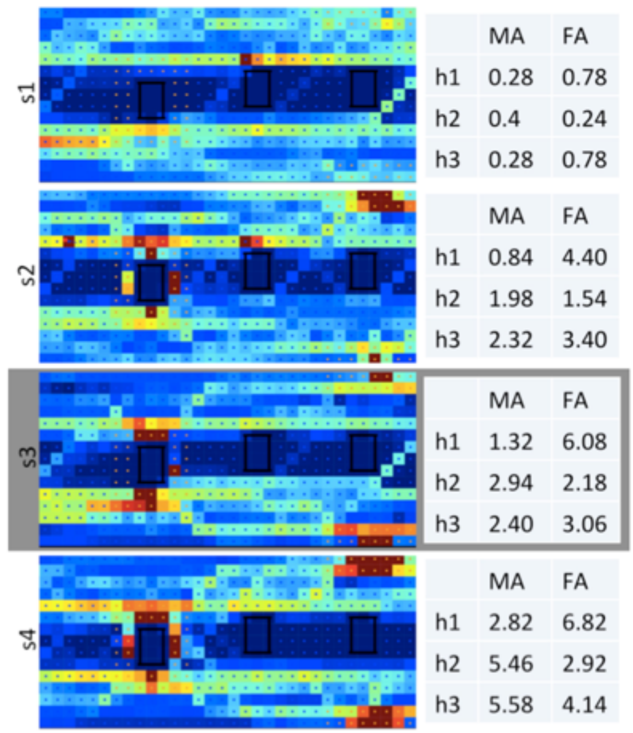


Figure 8 – Simulations results

4.2 Simularion Analysis

Simulation group s3 presented the best ajustment to the observed data. Higher values of MSA and FSA lead to higher attraction to hotspots. However, it is important to highlight that even though a pedestrian chooses a route to get closer to a shop window, he needs to reach a hotspot to stop. If the hotspot area is too crowded, he may not reach the hotspot, due to the social force effect, and do not stop. Thus, the attraction effect has a tendency to be balanced. Figure 9 show the s3 color map and the color map generated from real data. The s3 color map is one of 50 simulations. It is possible to observe differences in color patterns between simulation and real data. This difference is due the noise of pedestrians' tracking process and camera perspective. It is important to highlight stopping pattern at hotspots is similar.

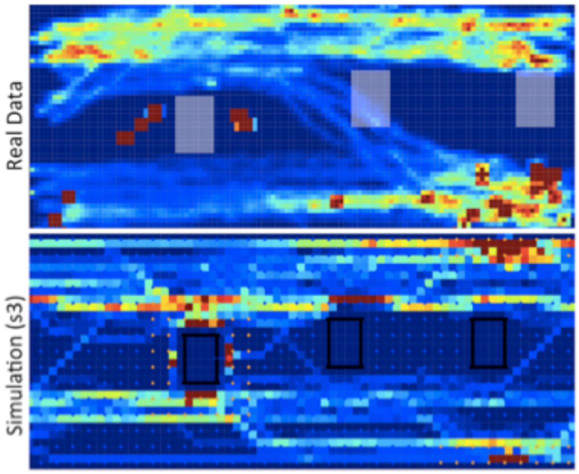


Figure 9 – Real data versus simulation data

5 Conclusions

The modeling approach presented in this paper provides a sound representation of pedestrian route choice dynamics considering the attraction to shop windows. Route choice is based on a combination of distance, impedance generated by other pedestrians and shop window attraction. The model differs from other pedestrians' route choice approaches because it seamlessly incorporates pedestrians social force into the route choice decision process.

In this model, we have created an association between the pedestrian's profile and store segment. When a pedestrian defines a route, due to its attraction to a store, he draws his chance to stop at a hotspot. The formulation of stopping chances can be enhanced through a more complex agent abstraction. However, it is well known that increasing model complexity usually leads to an increase in the calibration process effort.

The analysis from simulations indicates that the agents' emerging behavior provides a promising approach for real case applications. This model formulation is capable of supporting more complex agents' profiles and aplications to different enviroments, such as variable shopping premisses, expositions sites and passengers terminals.

Acknowledgments

The authors wants to thank the financial supported by the National Council for the Improvement of Higher Education (CAPES) and National Council for Scientific and Technological Development (CNPq), both of Brazil.

References

[Klügl, F., & Bazzan, A. L., 2012] Agent-based modeling and simulation. *AI Magazine*, *33*(3), 29.

[Macal, C. M., & North, M. J., 2006] Introduction to agent-based modeling and simulation. In *MCS LANS Informal Seminar*.

[Rossetti, R. J., Bordini, R. H., Bazzan, A. L., Bampi, S., Liu, R., & Van Vliet, D., 2002] Using BDI agents to improve driver modelling in a commuter scenario. *Transportation Research Part C: Emerging Technologies*, *10*(5), 373-398.

[Gaud N, Galland S, Gechter F, et al., 2008] Holonic multilevel simulation of complex systems: application to real-time pedestrians simulation in virtual urban environment. Simul Model Pract Theory 2008; 16: 1659–1676.

[Hoogendoorn S, Bovy P and Daamen W., 2002] Microscopic pedestrian wayfinding and dynamics modelling. In: Schreckenberg M and Sharma S (eds) Pedestrian and evacuation dynamics. Berlin: Springer, 2002, pp.123–155.

[Pretto CO, Jacobsen AC and Cybis H B B. 2011] A multi-layer simulation model for vehicle and pedestrian. In: Proceedings of the 90th Annual Meeting of the Transportation Research Board, Vol. 1, Washington, 2011, pp.1–15.

[Helbing D., 1991] A mathematical model for the behavior of pedestrians. Behav Sci. 1991; 36: 298–310.

[Helbing D and Molnar P., 1995] Social force model for pedestrian dynamics. Phys Rev E Stat Phys Plasmas Fluids Relat Interdisciplin Top 1995; 51: 42–82.

[Kirik ES, Yurgel'yan TB and Krouglov DV., 2009] The shortest time and/or the shortest path strategies in a pedestrian dynamics model. J Siberian Fed Univ Math Phys 2009; 2: 271–278.

[Dressler D, Groß M, Kappmeier J, et al. 2010] On the use of network flow techniques for assigning evacuees to exits. Procedia Eng 2010; 3: 205–215.

[Lämmel G and Plaue M., 2014] Getting out of the way: collision avoiding pedestrian models compared to the real world. In: Weidmann U, Kirsch U and Schreckenberg M (eds) Pedestrian and evacuation dynamics 2012. Berlin: Springer, 2014.

[Papadimitriou E., 2012] Theory and models of pedestrian crossing behaviour along urban trips. Transp Res Part F Traffic Psychol Behav 2012; 15: 75–94.

[Kretz T, Große A, Hengst S, et al., 2011] Quickest paths in simulations of pedestrians. Adv Complex Syst 2011; 14: 733–759.

[Kretz, T., Lehmann, K., Hofsäß, I., & Leonhardt, A., 2014] Dynamic assignment in microsimulations of pedestrians. arXiv preprint arXiv:1401.1308

[Crociani, L., & Lämmel, G., 2016] Multidestination Pedestrian Flows in Equilibrium: A Cellular Automaton-Based Approach. Computer Aided Civil and Infrastructure Engineering, 31(6), 432-448.

[Patil S, Van Den Berg J, Curtis S, Lin MC and Manocha D., 2010] Directing crowd simulations using navigation fields, IEEE Trans Visualization Comput Graphics 2010; 17(2): 244–254.

[Treuille A, Cooper S and Popovic Z., 2006] Continuum crowds. ACM Trans Graphics 2006; 25(3):1160–1168.

[Teknomo K. 2008., 2008] Modeling mobile traffic agents on network simulation. In: Proceedings of the 16th annual conference of the Transportation Science Society of the Philippines (TSSP), Manila, 2008.

[Teknomo K, Bauer D and Matyus T., 2008] Pedestrian route choice self-organization. In: Proceedings of the 3rd international symposium of simulation in transportation, Gold Coast, Australia, 2008.

[Wang, W. L., Lo, S. M., Liu, S. B., & Kuang, H. 2014] Microscopic modeling of pedestrian movement behavior: Interacting with visual attractors in the environment. Transportation Research Part C: Emerging Technologies, 44, 21-33.

[Dijkstra, J., Timmermans, H. J., & de Vries, B., 2013]. Activation of shopping pedestrian agents—Empirical estimation results. Applied Spatial Analysis and Policy, 6(4), 255-266.

[Borgers, A., & Timmermans, H., 1986]. A Model of Pedestrian Route Choice and Demand for Retail Facilities within InnerCity Shopping Areas. Geographical analysis, 18(2), 115-128.

[Ali, W., & Moulin, B., 2006]. How artificial intelligent agents do shopping in a virtual mall: A 'believable'and 'usable'multiagent-based simulation of customers' shopping behavior in a mall. In Advances in Artificial Intelligence(pp. 73-85). Springer Berlin Heidelberg.

[Werberich, B. R., Pretto, C. O., & Cybis, H. B. B., 2014] Pedestrian route choice model based on friction forces. Simulation, 0037549714547295.

[Helbing D, Farkas I and Vicsek T., 2000] Simulating dynamical features of escape panic. Nature 2000; 407: 487–490.

[Dijkstra E., 1959] A note on two problems in connection with graphs. Numer Math 1959; 1: 269–271.

[Dijkstra, J., Timmermans, H., Jessurun, J., & de Vries, B., 2014]. Modeling Time Duration of Planned and Unplanned Store Visits in a Multi-Agent Simulation of Pedestrian Activity in City Centers. In Pedestrian and Evacuation Dynamics 2012 (pp. 815-823). Springer International Publishing.

[Oppewal, H., & Timmermans, H., 1999] Modeling consumer perception of public space in shopping centers. Environment and Behavior, 31(1), 45-65.

7. CONCLUSION

This work proposed a computational model for pedestrians' simulation to represents urban environments. The literature review showed that the simulation of pedestrians with the decision-making process modeled in different layers leads to more realistic results. Throughout the development of this Doctoral Thesis the modeling of the pedestrian agent gained complexity in each of its decision-making layers.

Figure 3 shows, in a simplified way, the decision-making process of the agent. The agent makes decision based on its profile, its internal processes and the information it captures from the environment. The agent profile comprises all the settable parameters. Changes made to these parameters allow the representation of particularities of a pedestrian, such as: Adults, children, elderly, panicking pedestrians, pedestrians in a hurry, pedestrians interested in a certain type of environmental attraction and so on. The agent's internal processes define how the pedestrian reacts by combining the information in his profile with the information captured from the environment.

In the proposed model the final travel destination is assigned to each agent. In the same way, a map is given to the agent, in the form of a graph covering the scenario completely. All other information required by the agent decisions is collected at simulation time in its operational layer. The data collected by the agent are: the position and speed of other pedestrians, the presence of attractors in the environment and obstacles. All the information collected by the agent corresponds to data collected for real pedestrians. Orientations and desired direction of motion are not externally assigned to the agent.

Figure 3 shows the strong interdependence between the three decision layers of the agent. Perceptions of the pedestrian at the operational level trigger strategic and tactical decisions, which in turn, reflect on different behaviors at the operational level.

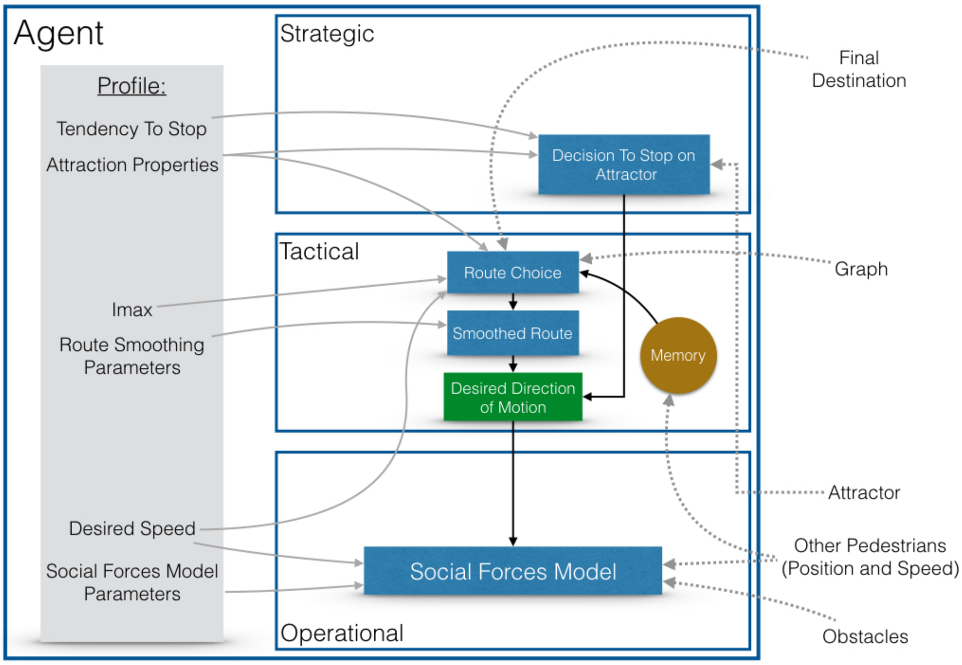


Figure 3 – The Agent Internal Process, Profile and External Data

Proposed model was able to reproduce pedestrian behaviors observed in experimental environment and in a real environment. The model shows promising when applied in simulation of urban environments.

7.1 Contributions

Complementing Figure 2 presented in Section 1, Figure 4 classifies the contributions of the papers presented on this Doctoral Thesis.

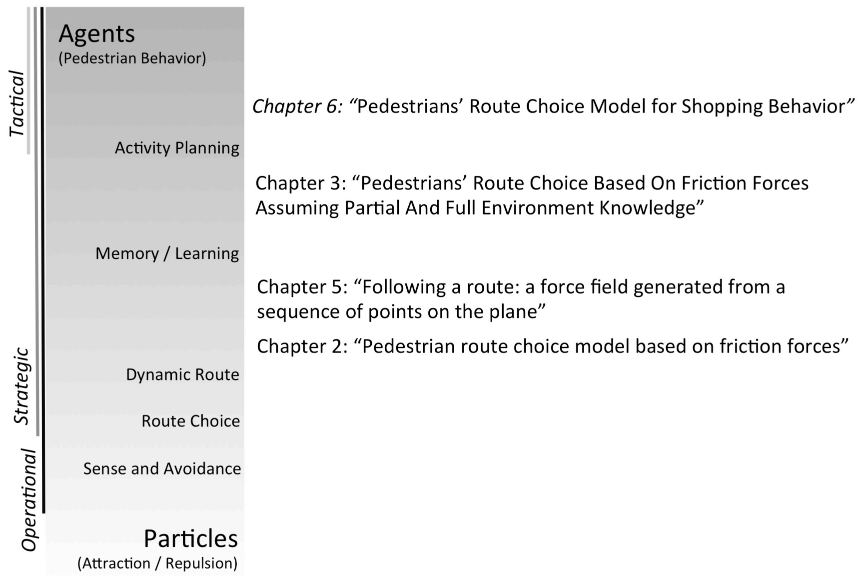


Figure 4 – Contributions

The paper presented in Chapter 2 describes a route choice model that considers the tendency of pedestrians to avoid conflicting flows. Other works presented in the literature reproduce the phenomenon by grouping pedestrians with common destinations into distinct groups, a simplification that can lead to unrealistic behavior in environments with complex geometry, and does not apply to simulations where pedestrians have distinct destinations. To represent the tendency to avoid conflicting flows, the model described in Chapter 2 uses the concept of Friction Forces. In this model the pedestrian chooses his route in order to minimize the friction with other pedestrians.

In Chapter 5 it is proposed a mathematical method to smooth routes generated on a regular graph. The method uses Bezier curves for stroke smoothing. In addition to smoothing the route, the model provides the agent orientation vector, similar to the Floor Field models. In Floor Field models the following direction is calculated for several points in the scenario, sometimes dynamically, in order to minimize congestion. In the proposed model the pedestrian calculates only one orientation vector for each simulation step, allowing each pedestrian to have a different route. At each point of the plane it is possible to calculate an orientation vector, in a non-discretized way, giving smoothness and realism to the pedestrian movement. In the proposed method the pedestrian does not calculate orientation vectors on the whole scenario, calculates only for its position, reducing computational costs.

In Chapter 3 presented paper describes pedestrians with limited knowledge about the state of the network, his knowledge is limited to the links already traveled. This approach eliminates unrealistic behaviors of super-organization of conflicting flows of pedestrians. The memory of the pedestrian in the proposed model is episodic, it exists only during a pedestrian trip, knowledge is not stored.

Chapter 4 of this document describes an experiment designed for data collection and observation of real pedestrians in a controlled environment. The data collected guided the calibration and validation of the proposed model.

The paper presented in Chapter 6 proposes a model able to represent the behavior of pedestrians in a shopping mall. In the proposed implementation the agent is able to make strategic decisions based on its perception of the environment at the operational level. The simulation results represent behaviors observed in real environment. The model shows promise in representing the attraction of pedestrians by areas of interest as well as the decision to stop at these attractors. This paper represents pedestrians as proposed on Chapter 5, with smooth routes. The urban environments representation is assessed on this paper once pedestrians have individual profiles, distinct destinations and can be attracted by interesting areas on the environment.

7.2 Future Works

The representation of pedestrians by computational models is a difficult task and can lead to the conception of models of extreme complexity. To correctly guide the design and evolution of simulation models it is necessary to make new observations of real pedestrians and to perform more accurate data collection. Vasconcelos et. al. (2013) [21] Describe the collection of pedestrian trajectories in laboratory automatically using ultra-wide band tags.

Further studies on the limitations of pedestrian awareness on the state and geometry of the network are needed. A real pedestrian often does not fully know the scenario to which he is inserted. In these situations the pedestrian is guided by intuition, observation of the flow of pedestrians and also by the sigs available in the environment.

The model flexibility allows the inclusion of new attributes for the pedestrian profile as well as the pedestrian's ability to perceive new elements present in the environment. Some common elements perceived by pedestrians include for example: altitude, quality of paving, interaction with vehicles, signs, among others.

REFERENCES

[1] Papadimitriou, E., Yannis, G., & Golias, J. (2009). A critical assessment of pedestrian behaviour models. Transportation research part F: traffic psychology and behaviour, 12(3), 242-255.

[2] Dijkstra, J., Timmermans, H., and de Vries, B. (2000). Towards a multi-agent system for visualising simulated behaviour within the built environment. In Proceedings of Design and Decision Support Systems in Architecture and Urban Planning Conference: DDSS (pp. 101-117).

[3] Helbing, D., and Molnar, P. (1995). Social force model for pedestrian dynamics. Physical review E, 51(5), 4282.

[4] Dressler, D., Groß, M., Kappmeier, J. P., Kelter, T., Kulbatzki, J., Plümpe, D., and Temme, S. (2010). On the use of network flow techniques for assigning evacuees to exits. Procedia Engineering, 3, 205-215.

[5] Kirik, E., Yurgel'yan, T. Y., and Krouglov, D. (2009). The shortest time and/or the shortest path strategies in a CA FF pedestrian dynamics model. arXiv preprint arXiv:0906.4265.

[6] Kretz, T., GROßE, A. N. D. R. E. E., Hengst, S., Kautzsch, L., Pohlmann, A., and Vortisch, P. (2011). Quickest paths in simulations of pedestrians. Advances in Complex Systems, 14(05), 733-759.

[7] Crociani, L., Invernizzi, A., and Vizzari, G. (2014). A hybrid agent architecture for enabling tactical level decisions in floor field approaches. Transportation Research Procedia, 2, 618-623.

[8] Hartmann, D., Mille, J., Pfaffinger, A., and Royer, C. (2012). Dynamic medium scale navigation using dynamic floor fields. In Pedestrian and Evacuation Dynamics 2012 (pp. 1237-1249). Springer International Publishing.

[9] Löhner, R. (2010). On the modeling of pedestrian motion. Applied Mathematical Modelling, 34(2), 366-382.

[10] Dijkstra, E. W. (1959). A note on two problems in connexion with graphs. Numerische mathematik, 1(1), 269-271.

[11] Hart, P. E., Nilsson, N. J., and Raphael, B. (1968). A formal basis for the heuristic determination of minimum cost paths. IEEE transactions on Systems Science and Cybernetics, 4(2), 100-107.

[12] Kielar, P. M., Biedermann, D. H., Kneidl, A., and Borrmann, A. (2016). A unified pedestrian routing model combining multiple graph-based navigation methods. In Traffic and Granular Flow'15 (pp. 241-248). Springer International Publishing.

[13] Andresen, E., Haensel, D., Chraibi, M., and Seyfried, A. (2016). Wayfinding and cognitive maps for pedestrian models. In Traffic and Granular Flow'15 (pp. 249-256). Springer International Publishing.

[14] Kwak, J., Jo, H. H., Luttinen, T., and Kosonen, I. (2017). Jamming transitions induced by an attraction in pedestrian flow. arXiv preprint arXiv:1701.06909.

[15] Wang, W. L., Lo, S. M., Liu, S. B., and Kuang, H. (2014). Microscopic modeling of pedestrian movement behavior: Interacting with visual attractors in the environment. Transportation Research Part C: Emerging Technologies, 44, 21-33.

[16] Werberich, B. R., Pretto, C. O., and Cybis, H. B. B. (2014). Pedestrian route choice model based on friction forces. Simulation, 90(10), 1177-1187.

[17] Helbing, D., & Johansson, A. (2011). Pedestrian, crowd and evacuation dynamics (pp. 697-716). Springer New York.

[18] Werberich, B. R., Pretto, C. O., and Cybis, H. (2014). Pedestrians' Route Choice Based On Friction Forces Assuming Partial And Full Environment Knowledge. In Transportation Research Board 93rd Annual Meeting (No. 14-3067).

[19] Werberich, B. R., Pretto, C. O., and Cybis, H. B. B. (2015). Calibration of a Pedestrian Route Choice Model with a Basis in Friction Forces. Transportation Research Record: Journal of the Transportation Research Board, (2519), 137-145.

[20] Werberich, B. R., Pretto, C. O., and Cybis, H. B. B. (2016). Pedestrians' Route Choice Model for Shopping Behavior. 9th International Workshop on Agents in Traffic and Transportation. (CEUR Vol-1678)

[21] Vasconcelos, G., Petry, M., Almeida, J. E., Rossetti, R. J., & Coelho, A. L. (2013). Using UWB for human trajectory extraction. arXiv preprint arXiv:1303.4696.