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Microscopic Modeling and Simulation of Pedestrian Traffic

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Abstract

Walking is an environmentally friendly and important mode of transportation. It constitutes the first and last part of almost any trip, regardless of what the main mode of transport is, and is especially important in connection to public transport trips.

When designing public transport stations, and similar facilities with large and varying volumes of pedestrian traffic, it is advantageous to be able to predict the traffic conditions at the facility before it is built; discovering too late that the traffic at the facility is inefficient and perceived as uncomfortable may be very costly. To make these predictions we need accurate quantitative models of pedestrian traffic.

The foundation of this thesis is the development of a microsimulation platform for pedestrian traffic, the Pedestrian Traffic Simulation Platform (PTSP). The platform is based on the Social Force Model (SFM) and intended for evaluation of proposed designs of pedestrian facilities. A contribution of this thesis is a thorough documentation of the implementation of the PTSP.

An extensive literature review of previous research on the SFM revealed gaps in the methodology used to study the properties of the SFM and to interpret its results. This thesis proposes local performance measures to fill this gap. These measures are based on properties of the SFM, and enable quantitative analyses of the quality of service at pedestrian facilities. The proposed measures are applied to the simulation results of some basic scenarios, which reveal previously unknown properties of the SFM. These properties can be used to test the accuracy of the SFM.

Another gap in the literature was how to include waiting behavior in the SFM. This thesis shows that accurate modeling of waiting pedestrians is important for the accuracy of the simulation results, and proposes three different extensions to the SFM to model waiting behavior.

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Norrköping, November 2013
Fredrik Johansson

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Chapter I

Introduction

WALKING is our most basic mode of transport. It may not represent a large part of our daily traveled distance, but pedestrian traffic is an essential part of the traffic system. Efficient multi-modal travel would not be possible without efficient pedestrian traffic connecting the modes of transport. Walking also constitutes the first and last part of practically any trip, so the old Chinese proverb is true in a very literal sense.¹

Predicting the behavior of an isolated pedestrian is a matter of describing its destination and preferences regarding the route choice to the destination. This is far from trivial, but as we include more pedestrians and try to predict how they interact with each other, the complexity of the problem increases dramatically.

A frequent occurrence of pedestrian traffic, and the apparent complexity of the interactions within it, are enough to motivate an academic interest to understand the phenomenon. In addition to this, our understanding of pedestrian traffic is of practical importance when we plan our society. Quantitative models of vehicular traffic have for a long time been part of the process of planning traffic systems, from national level down to individual intersections. For road traffic, the need to have an as efficient system as possible is obvious, since each wasted second does not only waste a second for the driver, but also contributes to our destruction of the environment through the emissions of the vehicles, and the massive amount of infrastructure

¹*"A journey of a thousand miles begins with a single step", attributed to Laozi.*

needed. The need to plan for efficient pedestrian traffic has not been as urgent, since pedestrian traffic is no threat to our environment and the infrastructure needed is often modest. Thus, models and observations of pedestrian traffic have not received as much resources as those of vehicle traffic. As a consequence we know less of pedestrian traffic than of vehicular traffic.

The need for accurate models of pedestrian traffic will be further discussed in section 1.1, and the subject and method of this thesis will be motivated. Then, in section 1.2, the scientific contributions are summarized, the publications on which the thesis is based are presented, and the individual contribution of the author is specified. In section 1.3, notation and terminology used throughout the thesis are introduced. Finally, in section 1.4, the outline of the rest of the thesis is given.

1.1 Motivation

The subject of this thesis is modeling and simulation of pedestrian traffic, that is, representing pedestrian traffic in a mathematical framework and using this framework to produce virtual traffic as similar to the real traffic as possible. The main reason for doing this is that it allows us to study various traffic situations through their virtual representation more easily than it is to study the real traffic directly. This is especially useful when the traffic of interest does not yet exist, but should be predicted. During planning of new infrastructure for vehicle traffic, prediction of the future traffic situation is routinely made to prioritize among different projects and to design the system. Using the same approach for planning of pedestrian infrastructure is becoming more and more common, and for this to be successful, accurate models of pedestrian traffic are needed.

In the beginning of this chapter we indicated that the efficiency of pedestrian traffic has been seen as less important than that of vehicular traffic, and maybe rightly so. Why should we care about the efficiency of pedestrian traffic at all? This is of course a matter of opinion, but one reason to improve the efficiency of pedestrian traffic is the environmental damages caused by vehicle traffic. One of the most efficient, and presently available, ways to reduce the environmental impact of the transport system is to decrease the fraction

of trips made by private car. Since there seems to be limited political will to decrease the attractiveness of the private car, the obvious alternative is to increase the attractiveness of more environmentally friendly alternatives. Walking is only a feasible alternative to a minority of the trips made by car, but public transport is a feasible alternative to almost all trips.

All public transport trips include walking; from the origin to the public transport, and from the public transport to the destination. Often, public transport trips include a transfer between transports; a public transport network can not have a direct connection from each possible origin to each possible destination. A large part of these transfers occur at a central public transport interchange station, or, in larger cities, at one of several major interchange stations. The performance of a public transport interchange station therefore has a large influence over the performance of a complete public transport system; if it takes time or is uncomfortable to transfer between transports at the central station, this will affect most trips, and the attractiveness of public transport will be lower.

An important question is thus how to design an interchange station so that short and comfortable transfers between transports are possible. An obvious criterion is that the walking distance between all bus stops, railway platforms, and the like, should be short, which implies a compact station. But a compact station also implies less space per visitor, that is, increased risk of congestion, which leads to longer walking times between transports and a more uncomfortable environment. Therefore, designing a public transport interchange station is a nontrivial task and a compromise has to be made between short walking distances and sufficient space to move. To achieve this, the pedestrian traffic at the station has to be predicted. The traffic volumes at different places in a station vary strongly in time due to variations in entering traffic caused by the arrival and departure of public transport services. These variations is a complicating factor that has to be taken into account when designing a station, and simulation is one way to do this.

There are several different types of models available to simulate pedestrian traffic, some of which are described in chapter 2. The main focus of this thesis is devoted to one of these types of models, microscopic simulation. A simulation model is said to be microscopic

if the building blocks of the simulation directly represent individual entities in the real world. In the case of pedestrian microsimulation, the building blocks of the simulation are individual virtual pedestrians. Microscopic simulation is suitable for a number of reasons, but mainly because the pedestrian population is diverse:

- Pedestrians with varying properties and preferences affect the traffic in different ways.
- Pedestrians with varying properties and preferences are affected by a given traffic situation in different ways.
- Some pedestrians cannot use all parts of the infrastructure.

Another reason for using a microscopic approach is that some infrastructure elements are sensitive to the granularity of pedestrian flow, for example narrow passages where only one pedestrian can pass at a time.

1.2 Contributions

The research presented in this thesis has resulted in a number of scientific contributions summarized below.

- The literature review over the current state of the Social Force Model (SFM) is a contribution in that it summarizes the current understanding of the SFM to an, to the best knowledge of the author, unprecedented extent.
- The development and thorough documentation of a complete SFM based simulation platform is a contribution in that it to a high level of detail describes the modeling assumptions and practical issues of such a framework.
- The local performance measures of pedestrian traffic is a contribution in that they improve our ability to describe pedestrian traffic and evaluate the quality of service at pedestrian facilities.
- By application of the local performance measures to simulation results, two nontrivial features of the SFM were revealed. Simulated pedestrians drift significantly in the direction of a crossing

flow and in some areas the time averaged local delay is negative. These two observations are contributions in that they describe previously undocumented properties of the SFM, which can be used to test the accuracy of the model.

- The development of extensions to the SFM to include waiting behavior, and the estimation of the importance of doing this, are contributions in that they show that in simulations of facilities where there are waiting pedestrians, the accuracy of the result is limited unless accurate models of waiting pedestrians are included.

Most of the material in this thesis has been submitted to journals for publication,

1. Johansson, F., Peterson, A., and Tapani, A. (2012). "Performance evaluation of railway platform design using microscopic simulation". In: *Proceedings of CASPT12*. Santiago, Chile.

A revised version of the paper, entitled "Local performance measures of pedestrian traffic" is under review for publication in a special issue of *Public Transport* dedicated to papers presented at CASPT12.

2. Johansson, F. (2013). *Pedestrian traffic simulation platform*. VTI notat 16-2013. Swedish National Road and Transport Research Institute, Linköping.
3. Johansson, F., Peterson, A., and Tapani, A. (2014). "Waiting pedestrians in the social force model". *Under revision for probable publication in: Physica A Statistical Mechanics and its Applications*.

The author of this thesis has contributed to these papers as main author and by major involvement in research planning, modeling, software design and implementation, performing simulations, and analyzing results.

Parts of the results have also been presented by the author at the following conferences:

1. Transportforum, Linköping, Sweden, January, 2012,

2. CASPT12, Santiago, Chile, July, 2012,
3. Nationella konferensen i transportforskning, Stockholm, Sweden, October, 2012,
4. Transportforum, Linköping, Sweden, January, 2013,
5. Nationella konferensen i transportforskning, Gothenburg, Sweden, October, 2013.

1.3 Notation and terminology

In this thesis both simulated and real pedestrians have a central role. For simplicity, the objects which represent pedestrians in the models and simulations are called *walkers*, while the term *pedestrian* is reserved for real pedestrians.

Vectors are denoted by lowercase bold letters, such as $\mathbf{x}$ and $\mathbf{a}$, and their lengths are denoted by the corresponding non bold letters, that is, $x = |\mathbf{x}|$, $a = |\mathbf{a}|$. Vectors belong to $\mathbb{R}^2$ if nothing else is stated. The time derivative is denoted by a dot, that is, $\dot{x} = \frac{dx}{dt}$.

A list of abbreviations is included on the last page of the thesis.

1.4 Outline

The thesis is structured as follows. In chapter 2 an introduction to, and literature review of, pedestrian simulation is presented. The review is focused on the applicability of the reviewed models to simulation of pedestrian traffic under normal conditions, but also mentions other possible applications of the models.

The general review in chapter 2 is followed in chapter 3 by a more detailed description of the pedestrian simulation model which the focus of this thesis is devoted to: the SFM. Here the development of the SFM, from its inception in the early nineties to the several versions and extensions that exist today, is presented. Also, in the same chapter, we see how the SFM fits into a larger simulation framework, and also describe the general properties and predictions of the SFM.

To enable the simulation of waiting pedestrians, a series of extensions to the SFM is proposed in chapter 4.

When the SFM has been properly introduced we dive into the details of implementing a SFM based simulation platform in chapter 5, where the purpose, development strategy, and specification of the Pedestrian Traffic Simulation Platform (PTSP) are presented.

In chapter 6 the advantages and disadvantages of different ways to quantitatively characterize pedestrian traffic are discussed, and new measures are proposed. These new *local measures* are able to overcome some of the limitations of the traditional measures.

Finally, in chapter 7, the application of the local measures to the results of a series of simulations performed using the PTSP is shown to provide nontrivial predictions of the SFM. It is also confirmed that the waiting models proposed in chapter 4 produce the expected behavior, and the differences between them are clarified.

The thesis is concluded in chapter 8 with a discussion based on the presented work and some thoughts on the directions of future research.

Chapter 2

Models of pedestrian traffic

QUANTITATIVE modeling of vehicular traffic has a long history, initiated by the early recognition that the exploding use of private cars resulted in huge infrastructure investments, which needed careful planning. Later, when the magnitude of environmental impact of car traffic became apparent, the importance of accurate models of traffic grew further. Modeling of pedestrian traffic was of course of secondary importance, simply because the infrastructure was cheap, there were no big capacity problems, and pedestrians do not destroy the environment. The most important applications for motivating research on pedestrian modeling have been the cases when inefficient pedestrian traffic is dangerous, evacuation and panic situations.

Significant progress within the field of pedestrian modeling has been made the last three decades, and in many cases by translating insights from car traffic modeling to a pedestrian setting. This translation is however nontrivial, mainly due to one fundamental difference between car traffic and pedestrian traffic: pedestrian traffic is almost always two dimensional, while car traffic often can be regarded as effectively one dimensional. The dimensionality of the problem influences its properties at all levels, from algorithmic complexity to data collection. This is the main reason that it is easier to model car traffic compared to pedestrian traffic.

The reasons for modeling pedestrian traffic have been discussed in chapter 1, but note again the importance of capturing the dynamics

of pedestrian traffic. The importance of this, among other things, has led to a difference in the kind of models that has been developed for pedestrian traffic compared to car traffic; there are hardly any static equilibrium models of pedestrian traffic assignment because the dynamics is often deemed too important to omit.

When it comes to applications to real problems, the traditional methods used to model pedestrian traffic have been empirically based relations for the capacity of bottlenecks and level of service of limited elements of pedestrian facilities, such as those presented by Kittelson & Associates, inc. et al. (2003). The level of service of an area is a categorization of the traffic conditions into six levels, based on the average density and flow in the area; this categorization goes back to Fruin (1971). Kittelson & Associates, inc. et al. (2003) further presents volume – density relations for both walkways and stairs and capacities for different kinds of doors and escalators.

Such simple approximations are very important and useful for specifying the capacity of individual elements of the infrastructure, but are of limited use when evaluating the performance of complex facilities since the variations in the traffic volumes become harder to estimate as the complexity of the studied facility increases.

The review of different modeling approaches presented in this chapter is in no way intended to be complete; it is merely meant to indicate the most commonly occurring approaches and to give typical concrete examples for each approach. Traffic models are usually categorized according to the scale of the variables of the model: Macroscopic, microscopic, and mesoscopic. The present chapter follows this categorization.

2.1 Macroscopic models

Macroscopic models model the macroscopic, or average, properties of the system directly, without any explicit reference to its underlying microscopic nature. A central assumption of macroscopic models is thus that no, or sufficiently little, significant information is lost when the microscopic details are averaged out. The method has been successful in physics, where the assumption is founded on the extreme difference in scale between the microscopic and macroscopic phenomena, and on the immense number of microscopic degrees of free-

dom corresponding to a macro state.

The assumption is less well founded in traffic modeling compared to standard physics applications, which can easily be seen by considering the number of microscopic entities involved. However, it has been proven to be successful in modeling of car traffic, so there is good reason to expect similar success for pedestrian modeling. One should, however, always keep the assumptions in mind when interpreting the results of macroscopic models.

The continuum dynamic approach to traffic modeling assumes that traffic can be regarded as a fluid, or continuum, disregarding the fact that it is composed of discrete entities such as cars or pedestrians. Equivalently one can see the fluid dynamic approach as a model of the average, or expected, values of the variables describing the macroscopic states of the traffic, assuming that the deviations from the expected values due to the discreteness of the traffic is too small to be important for the applications in mind.

The basis of fluid dynamic models of pedestrian traffic is the two dimensional continuity equation,

$$\frac{\partial \rho}{\partial t} + \nabla \cdot \mathbf{q} = 0, \quad (2.1)$$

where ρ is the mean density, and $\mathbf{q} = \rho \mathbf{u}$ is the mean flow, both functions of time and space, and the assumption that the mean speed, u , is a function of the density, that can be obtained from observations.

An early application of the approach was AlGadhi and Mahmasani (1990, 1991), who applied a discretized version of the theory to simulate the religious rites at the Jamarat bridge during the annual pilgrimage to Makkah. The simulated scenario consists of pilgrims approaching a stone pillar, and then after performing the ritual moving away. This leads to a two population model, one population of walkers with the stone pillar as destination and another population consisting of walkers that already performed the ritual. The continuity equation is then valid for each type of walker separately, but modified by a source/sink term describing the transition of walkers of the first population into the second. The speed of one population in the radial direction is assumed to depend on both the density of itself and that of the other population, in a symmetric manner. The flow in the angular direction, however, inspired by work on the diffusion of cars between lanes in multi-lane highway traffic, is assumed

to be proportional to the gradient of the total density above a certain threshold. The form of both the speed density function and the transition process is obtained from observations.

Inspired by the success of continuum theory to describe vehicular traffic, Hughes (2000, 2002, 2003) generalized the arguments of Lighthill and Whitham (1955) to two dimensional pedestrian traffic in general. He considers the multi population continuity equations

$$\frac{\partial \rho_\alpha}{\partial t} + \nabla \cdot \mathbf{q}_\alpha = 0, \quad (2.2)$$

where ρ_α and $\mathbf{q}_\alpha$ are the density and specific flow respectively of a population α and

$$\rho = \sum_\alpha \rho_\alpha \quad (2.3)$$

is the total density, and assumes that the speed of population α is a function only of the total density. The definition of a population is the same as in AlGadhi and Mahmassani (1990, 1991), all walkers of the same population share the same destination. Further it is assumed that for each population α , there is a potential, ϕ_α , such that all walkers in α walk in the direction of the negative gradient of the potential,

$$\mathbf{u}_\alpha = -u_\alpha(\rho) \frac{\nabla \phi_\alpha}{|\nabla \phi_\alpha|}. \quad (2.4)$$

The potential is depending on the speed – density relation through

$$|\nabla \phi_\alpha| = \frac{1}{u_\alpha(\rho)}, \quad (2.5)$$

which means that the potential is a measure of the remaining travel time to the destination. Equations (2.2) to (2.5) together with boundary conditions suitable to describe the infrastructure is sufficient to describe the evolution of the pedestrian density in the area.

Assuming a linear velocity density relation, as Greenshields et al. (1935) did for vehicle traffic, Hughes (2002) showed that two different traffic states occurs, and that perturbations behave analogous to the theory of Lighthill and Whitham (1955).

The central assumption simplifying the above theory is the assumption of a speed – density relation depending on the total density only. This implies that walkers are not affected by the relative

direction of the surrounding walkers, they walk equally comfortably opposing a flow as with a flow, or at an angle of a flow.

Jiang et al. (2010) extended the model, in analogy to second order vehicle traffic models, by including an equation for momentum conservation in addition to the continuity equation,

$$\frac{\partial \mathbf{q}}{\partial t} + \nabla \cdot (\mathbf{q} \otimes \mathbf{u}) = \frac{\rho}{\tau} (\mathbf{v}^p - \mathbf{u}) - \nabla p(\rho), \quad (2.6)$$

where p is a repulsive crowd pressure and $\mathbf{v}^p$ is the preferred velocity replacing $\mathbf{u}$ in equation (2.4), thereby making the velocity $\mathbf{u}$ a dynamic variable. The first term in the right hand side represents the desire of pedestrians to move with a preferred speed, v^p , toward the destination, and the second term their dislike of walking too close to each other. The form of the term describing the adaptation toward the preferred velocity is taken from the SFM, equation (3.1). A numerical scheme to solve the model is presented and applied to an example scenario, where the model is shown to produce stop and go waves that the first order model does not exhibit.

Recently Twarogowska et al. (2013) further compared the two models and showed that the second order model produces clogging at bottlenecks, and reproduces the pedestrian version of Braess' paradox: unidirectional flow through a bottleneck may be increased by placing an obstacle in front of it.

2.2 Microscopic models

Microscopic models describe every individual walker and its interaction with other walkers and the environment. This means that, in contrast to the macroscopic approach, there is no averaging process that results in loss of detail, and the heterogeneity of the population can be explicitly included in the model.

The microscopic models can be roughly categorized into four types: cellular automaton based models, agent based models, game theoretic models, and force based models. These categories are partially overlapping and not well defined. For example, all microscopic models could be regarded as agent based; still the categories are useful to discuss some aspects of the models.

Cellular Automata (CA) based models are discrete in space and time, and were in the early days the only practical microscopic simulation models, due to the limited computational power. Each spatial unit is called a cell, and can either be occupied by one pedestrian or obstacle, or be empty. This means that the size of a walker is fixed and constant over the population and also that there is a minimum movement that can be made, movements must be at least one cell at a time. The spatial discretization is of course a crude approximation, but the gain in computational efficiency can be substantial compared to a continuous space representation, which is the main advantage of CA models. Another advantage is that for simple update rules, some general properties of the models are possible to obtain analytically.

An early cell model of pedestrian traffic at the microscopic level was presented by Gipps and Marksjö (1985) who use a grid with quadratic cells with side 0.5 m and let a walker consider its Moore neighborhood, the eight neighboring cells and its present location, for the next move. The preferred next cell is the one that reduces the remaining distance to the walker's destination the most. The navigation is however modified by the presence of other walkers, according to the idea of a repulsive potential around each walker. The potential in a cell is the sum of the potential from all walkers, and when deciding to which cell to move, the walker subtracts the potential of each neighboring cell from the respective gained distance associated with each cell, and then moves to the cell with the highest value. To allow for different speeds of the walkers the authors use a sequential update scheme where fast walkers are allowed to move more often than slow walkers. This sequential update scheme also avoids the need for conflict resolution rules which is necessary for parallel update schemes.

The need to introduce long range interactions between pedestrians to produce collective phenomena, such as dynamic lane formation, prompted Schadschneider (2001) and Burstedde et al. (2001a,b) to introduce a dynamic floor field with its own dynamics. This allows for computationally efficient solution of the model by letting each walker only interact *directly* with its immediate surroundings, and interact *indirectly*, through the floor field, with walkers further away. The dynamics of the floor field are also local, so that each part of the model becomes independent of the situation in other parts.

The purpose of introducing a dynamic floor field is to produce lane formation by making cells where a walker recently passed more attractive to walkers with the same walking direction, and letting the strength of this influence decrease with time. This means that dynamic lane formation is explicitly included in the model, instead of emerging from more fundamental behavioral rules, as in the *SFM*, where the emergence of dynamic lane formation and similar phenomena are strengthening the confidence in the model. The model is stochastic, expressing the preferences of the walkers as probabilities for the next move, as seems to be the most common in modern *CA* models of pedestrian traffic. The update procedure is parallel, which is more intuitive than the sequential update scheme in Gipps and Marksjö (1985), but introduces the need to resolve the conflicts that appear when two or more walkers attempt to move to the same cell. This is solved by another random draw, using the previously calculated probabilities of the conflicting walkers as relative probabilities to determine which walkers that are allowed to move; the others stay.

But the conflicts arising from the parallel update scheme may be seen as a feature of the model, rather than a problem, as Kirchner et al. (2003) point out. They introduce a friction parameter that determines the probability that none of the walkers involved in a conflict are allowed to move, and argue that the resulting model describes real traffic more accurately; for example, they observe *arching* at exits, that is, several walkers trying to get out at the same time, resulting in no movement.

Since only one walker can be in each cell in *CA* models, bidirectional flow in a corridor can reach a dead lock situation, with walkers lined up against each other, unable to move. This situation is unlikely at low densities, but becomes more likely at densities above a certain limit. This phase transition, from a state with nonzero flow, to the state with no flow, has been studied extensively in the literature, for example by Muramatsu et al. (1999), Muramatsu and Nagatani (2000), Tajima et al. (2002), and Ma et al. (2010).

Recent studies using *CA* models include Davidich et al. (2013), who use a *CA* with a hexagonal grid to investigate the importance of including waiting pedestrians in models of public transport interchange stations. Their results will be further discussed in chapter 4.

Even though the definition of CA varies among authors, at some point the update rules of a discrete model become too complex to be called a CA and the model becomes a discrete *Agent Based Model* (ABM); the models of Kretz (2007) and Still (2000) are examples of models in the borderland between CAs and ABMS.

In general, however, ABMS can be either continuous or discrete, both in space and time, and can be governed by practically any type of behavioral rules. ABMS often have a large set of behavioral rules, each dedicated to a specific situation. The update procedure occurs in two steps, the agent first determines the situation it is in by one or several test, and then executes the rule connected to that situation, see for example Usher and Strawderman (2010). ABMS can be very detailed, but this comes at a high computational cost (Klugl and Rindsfuser, 2007). Furthermore, due to the large number of behavioral rules, it is hard to analytically derive properties of ABMS.

Ondřej et al. (2010) call their model synthetic vision based, and the behavioral rules are almost too simple to call it an ABM, but in all other aspects it fits this classification. They base the model on research on the connection between the human vision system and collision avoidance by Cutting et al. (1995), that claims that a pedestrian determines if it is on a collision course with an object, another pedestrian, or an obstacle, by observing the time derivative of the bearing angle α of the object, defined as the angle between the direction of motion of the pedestrian and the direction from the pedestrian to the object. A walker is on collision course with an obstacle only if $\dot{\alpha}$ is close to zero. The time of interaction, t^I , is defined as the time at which the distance between the walker and the obstacle reaches its minimum, and is assumed to be accurately estimated by the walker by observing the rate by which the obstacle's apparent size is increasing. The authors explicitly model the field of view of each walker in a simplified geometry to determine which objects the walker is aware of. The field of view is in the direction of motion and 150° wide, so movements of the head that effectively increase the field of view are neglected. A walker reacts to objects that are within its field of view and has $\dot{\alpha} < \tau_1(t^I)$ and $t^I > 0$, where $\tau_1(t^I)$ is a given function that describes the threshold for when the walker regards an object as being on collision course. This threshold is larger for lower t^I , that is, if something soon will reach its closest encounter with the

walker it is more likely to receive the attention of the walker. The control variables are the angular velocity and the speed, with bounds on the corresponding accelerations. However, the speed of the walker is only reduced from the preferred speed if a collision is imminent. The explicit calculation of the field of view of each walker is computationally expensive, but as the authors note, the model is in principle applicable without this calculation, taking into account all objects in front of the walker, instead of only the visible.

A central part of any microscopic model is the collision avoidance behavior. Models of this behavior always include an assumption of the expectation of the walker of what other walkers will do next. In most models the walkers assume that the surrounding walkers will continue with constant velocity, that is, they make some version of a first order interpolation of the other walkers future position. An exception to this is the hierarchy of models outlined by Zanlungo (2007). Here, a walker will assume that surrounding walkers behave according to similar rules as itself, but slightly simplified. More exactly, in the model on level l in the hierarchy of models, a walker will assume that all other walkers behave according to the model on level $l - 1$. The recursion ends at the model on level 0 which consists of walkers that ignore each other, and physical interactions. Level one walkers thus assumes that all other walkers will ignore their surroundings and base their evasive maneuvers on this assumption. The idea is to subject the walkers to an evolutionary process, in which the walkers have the goal of reaching a destination as quickly as possible, while collisions are punished.

Antonini et al. (2006) and Robin et al. (2009) take a conceptually much simpler approach, applying discrete choice theory to the steering behavior of walkers. The choice set is generated by discretization of the choice of speed and the choice of direction by considering three alternatives for the speed and eleven alternatives for the direction, resulting in a nested logit model. This discretization can equivalently be seen as a local discretization of the space in front of each walker, with the choice of speed and direction corresponding to choosing a target cell. The choice of new speed is divided into three alternatives consisting of speed intervals represented by their midpoint: decelerating to half the current speed, keeping constant speed, or accelerating to 1.5 times the current speed. The choice of new direction is

discretized into 11 angular intervals, one centered along the current direction of motion and five on each side with larger intervals further out, and limited by the field of view of the walker. The utility function takes into account the distance to other walkers from the target cell, the angular change needed, the difference between the considered angle and the angle to the destination, the walking direction of other walkers, etc.

Guy et al. (2010) assumes that pedestrians walk according to the principle of least effort in the literal sense that they minimize the biomechanical energy spent, subject to the constraint that the motion should be collision free. For the spent power of the walkers they use an empirical result indicating that the power consumed by a human walking at constant speed is $P = a + b\dot{x}^2$, where a and b are constants. The optimization problem is approximately solved by first generating the set of short time collision free velocities of a walker by the method proposed by Van Den Berg et al. (2011). Then the velocity in this set that minimizes the remaining energy needed to reach the goal is chosen, assuming that the chosen velocity will be kept for a short period of time. The resulting behavior is consistent with known self organization phenomena, and the resulting walker trajectories are smooth. Note that these results are obtained without any cost associated with acceleration processes; the energy that is minimized is only the cost of walking at a constant speed, the cost of accelerating to this speed is neglected.

Both Guy et al. (2010) and Antonini et al. (2006) formulate the behavior of the walkers as that of cost minimizers, or equivalently utility maximizers, for some cost or utility function. Hoogendoorn (2001) applies this approach systematically on all levels of pedestrian behavior, assuming that both the large scale behavior, consisting of activity planning and route choice, and the operational behavior, consisting of evasive maneuvers, should be seen as utility maximization processes. On the large scale, the choice of where to perform activities, and the choice of route between them, is assumed to be simultaneous, resulting in a comparison of the cost of all possible activity schedules, where each activity schedule consist of an ordered sequence of route choices. The route $x(t)$ chosen to an activity loca-

tion is the one that minimizes the generalized cost

$$J = \Phi[T, \mathbf{x}(T)] + \int_t^T (a + b\dot{x}^2 + f(\mathbf{x})) dt', \quad (2.7)$$

where a and b are model parameters, T is the planning horizon of the walker, $f(\mathbf{x})$ is a function over the walkable area representing the cost of walking too close to fixed obstacles, and $\Phi[T, \mathbf{x}(T)]$ the utility of reaching the destination (if it is reached). The walkers are assumed to control their velocity optimally to minimize equation (2.7) under the constraint of a maximal velocity possibly depending on the position. The problem is solved by constructing the value function, representing the optimal cost needed to get to the destination, from the last destination and backwards. This is similar to the construction of the navigation potential ϕ , equation (2.5).

On the operational level of the model, walker i is assumed to minimize the cost

$$J_i = \int_t^\infty e^{-\eta t'} \left(\alpha \frac{|\mathbf{v}_i^p - \dot{\mathbf{x}}_i|^2}{2} + \beta \frac{|\ddot{\mathbf{x}}_i|^2}{2} + \gamma \sum_j V(\mathbf{r}_{ij}, \dot{\mathbf{r}}_{ij}) \right) dt', \quad (2.8)$$

where η is a discount factor taking into account that what may happen in the future is less important, $\mathbf{v}_i^p$ is the preferred, optimal, velocity from the higher level navigation, $\mathbf{x}_i$ is the position of the walker, $\mathbf{r}_{ij}$ is the position of walker i relative to walker j , and V is a function describing the cost of being close to other walkers. The first term represents the cost of deviating from the planned optimal velocity, and the second the cost of accelerating or decelerating. The control variable of the walker at the operational level is its acceleration, which implies that it will have some inertia contributing to the smoothness of its path. The optimal acceleration is obtained by minimization of equation (2.8), through calculus of variations and assuming that there is no explicit time dependence in the running cost in addition to the discount factor. The resulting optimal acceleration becomes

$$\ddot{\mathbf{x}}_i^* = \left(I - \frac{1}{\eta} \frac{\partial \mathbf{v}_i^p}{\partial \mathbf{x}}^T \right) \left(\frac{\mathbf{v}_i^p - \dot{\mathbf{x}}_i}{\tau} \right) - \zeta \sum_j \left(\frac{\partial V}{\partial \mathbf{r}_{ij}} + \eta \frac{\partial V}{\partial \dot{\mathbf{r}}_{ij}} \right), \quad (2.9)$$

where I is the unit matrix, $\tau = \eta\beta/\alpha$, and $\zeta = \gamma/\beta\eta^2$. The first term represents the adaptation to the optimal velocity of the higher

level route choice, and the second term represents the reaction to surrounding walkers. Note that the first term, except for the factor correcting for the spatial variation of the optimal velocity, has the same form as the corresponding term in the second order macroscopic model, equation (2.6). Possible forms of V are discussed, including an anisotropic scaling to represent that pedestrians react stronger to things in front of them.

Hoogendoorn and Bovy (2002) discuss the inclusion of an observation model to describe how the walkers estimate the current state of the traffic, and extends the acceleration cost term in equation (2.8) to differ between longitudinal and lateral acceleration. The emergence of dynamic lane formation in bidirectional flow, and dynamic stripe formation in crossing flows are demonstrated. Also, the importance of anisotropy is demonstrated by the derivation of an analytical expression for the density dependence of the speed of stationary homogeneous one-dimensional flow; without anisotropic reactions, the mean speed is always the optimal speed, regardless of density.

The model is extended further by Hoogendoorn and Bovy (2003) with the inclusion of the walkers expectations on the reactions of other walkers, and the inclusion of physical forces on the walkers in the cases of physical contact. This results in a second order term in equation (2.9) including both the derivatives of V and the derivatives of the expected accelerations of the other walkers. Hoogendoorn and Bovy (2004) explicitly includes the uncertainty of the walkers regarding the traffic conditions, by assuming that the walkers minimize the expected cost during route choice.

In the model by Hoogendoorn and Bovy, the walkers are assumed to be utility maximizers which enables the formulation of a systematic approach to describe the behavior. The utility theory is used as a foundation to derive operational rules in the form of accelerations in response to the surrounding. In contrast to this, many ABMS and CAS seem ad hoc, and lacking in analytical tractability; yet some models are able to produce remarkably realistic behavior using only a few simple rules, but without a theoretical behavioral framework. In between these extremes are the *force based models*, that describe the walkers in continuous space and model the reactions of the pedestrians to their surroundings in terms of a set of forces. These forces are in general not physical forces, but rather describe the various moti-

vations of the walkers, analogous to the terms in equation (2.9) for the acceleration.

The force concept provides a consistent framework for describing the desires of the walkers, and the close analogy with particle systems makes it possible to study limited systems analytically and reason about general properties of the models. Force based models are exclusively focused on modeling the operative behavior of pedestrians, that is, mainly evasive maneuvers, and require a representation of the chosen route as input, usually in the form of a vector field describing the preferred direction or velocity in each point of the walkable area. The desire to walk with this preferred velocity is in most cases represented by a force of the form

$$\mathbf{F}_i^p = \frac{m}{\tau} (\mathbf{v}_i^p - \dot{\mathbf{x}}_i), \quad (2.10)$$

where $\mathbf{v}_i^p = \mathbf{v}_i^p(\mathbf{x}_i)$ is the vector field describing the preferred velocity, $\dot{\mathbf{x}}_i$ is the current velocity of the walker, and m and τ are parameters with dimensions of mass and time, respectively. This is the same form as in the model by Hoogendoorn and Bovy except for the factor taking into account the variations in the field $\mathbf{v}_i^p$, and the same as in the second order macroscopic model, equation (2.6).

The first force based model of pedestrian traffic was probably the model proposed by Hirai and Tarui (1975), and was, according to themselves, inspired by a model of schools of fish by Suzuki and Sakai (1973)¹. Their purpose was to model the members of a panicking crowd during evacuation, by assuming an equation of motion of the form

$$m\ddot{\mathbf{x}}_i + \nu\dot{\mathbf{x}}_i = \mathbf{F}_{1i} + \mathbf{F}_{2i} + \mathbf{F}_{3i}, \quad (2.11)$$

where ν is a viscosity parameter, that is, $\nu\dot{\mathbf{x}}_i$ is a friction term; and $\mathbf{F}_1$, $\mathbf{F}_2$, and $\mathbf{F}_3$ are three categories of forces, representing interactions, environmental influence, and randomness, respectively.

The interaction force has in turn three terms, the first one is a constant force in the direction of motion, the second is an interaction term dependent on the relative position of the affecting walker, and the third is an interaction term dependent on the relative velocity of the affecting walker. Both the interaction terms are anisotropic, the

¹The article by Suzuki and Sakai (1973) is unfortunately in Japanese, but the equations are very similar to those used by Hirai and Tarui (1975)

force vanishes if the affecting walker is behind the affected and increases as the angle between the velocity of the affected walker and the direction to the affecting walker decreases.

The force category describing environmental influences consists of a repulsive wall force, and a set of constant forces directed toward the destination and away from the source of the panic.

Note that moving the viscous friction term from the left hand side of equation (2.11) to the right hand side and pairing it with the constant force directed toward the destination gives exactly the driving force, equation (2.10).

The most prominent force based model is the sFM proposed by Helbing and Molnár (1995), which will be presented thoroughly in chapter 3. Many versions of the sFM have been proposed, with a repulsive force between walkers that is exponentially decreasing with larger distance between the walkers as the common element. There are also other models, similar to the sFM, such as the centrifugal force model (Yu et al., 2005; Chraïbi et al., 2009, 2010).

2.3 Mesoscopic models

In *mesoscopic* models each individual is represented individually and can have individual properties, in contrast to the macroscopic view where an individual only is represented as a contribution to the mean density, and can not be followed from its origin to its destination. However, the individual walker's behavior is still determined by average quantities in mesoscopic models, in contrast to microscopic models where the walker's behavior is determined by the behavior of all the other walkers. The mesoscopic models are in this sense a compromise between macroscopic and microscopic models, trying to get the computational efficiency and analytical tractability of macroscopic models, but at the same time being able represent some of the diversity and individuality of real pedestrians.

One example is Treuille et al. (2006) who extended the model of Hughes (2000) to a hybrid simulation model with microscopic walkers navigating using a generalization of the potential ϕ . The simulation procedure consisted of first calculating a smooth density field from the locations of all walkers, then calculating a generalized cost field, analogous to $1/u$ in equation (2.5), followed by the calculation

of ϕ . The positions of the walkers are then updated according to the analogue of equation (2.4) and finally a minimum distance between the walkers are enforced by a brute force method. Also, by making the speed depend on the density slightly ahead of the walker, that is, in the direction of the mean velocity of the population, dynamic lane formation emerges.

The above model keeps track of the location of each pedestrian in continuous space and imposes a spatial exclusion principle, and is in this sense closely related to the microscopic models. In contrast the model by Daamen (2004) keeps track of the positions of the walkers at the level of links in a network representation of the pedestrian facility, and models the interactions of the walkers at a macroscopic level. The model is a mixed event based and time controlled simulation in which the route choice of the walkers in the network is updated at regular time intervals, while the arrival of the individual walkers to network nodes are governed by an event based approach. When a walker is about to start walking down a link in the network its travel time on that link is calculated based on link attributes derived from the detailed geometry of the infrastructure represented by the link, the current average walker density on the link, and the individual properties of the walker represented by its preferred walking speed. During the travel time on the link, the walker contributes to the average density on the link, but is not located in any higher detail than that. In this way the model is updated every time a walker arrives at a new node in the network, and individual walkers with individual properties are tracked throughout their passage through the network, without a computationally expensive continuous space representation of their location. Daamen (2004) does not just describe a modeling approach, but describes in detail a complete system specialized at simulating pedestrian traffic at public transport interchange stations with detailed specifications of the modeling of all commonly occurring elements of such facilities, thoroughly founded on empirical research.

Chapter 3

The social force model

WHEN you walk through a crowded area, how do you avoid collisions with other pedestrians? Do you reason how to take each and every step and predict how each of the surrounding pedestrians will move, or do you simply react to the environment spontaneously?

Helbing and Molnár (1995) argue that a force based approach to microscopic pedestrian simulation is suitable since people are used to walk in crowded environments and have developed good subconscious, or automatic, strategies for avoiding collisions and keeping comfortable distances to surrounding pedestrians. These automatic strategies should be possible to encode as simple behavioral rules based on the objectives of the pedestrians and the surrounding conditions. The main idea of the SFM is to describe the influences of elements of the environment on the behavior of the pedestrian as *social forces*. These forces are of course not forces in the strict Newtonian meaning, rather, they are a description of the motivation, or desire, of the pedestrian to change its velocity, induced by some elements in the environment. The physical, observable, result of this motivation is that the pedestrian applies an acceleration to control its motion, thus motivating the term ‘force’.

Another motivation for the name is that the effects of several social forces, just like regular forces, are assumed to add as vectors. This assumption is the core of the simplicity of the SFM, but at the same time it is also one of the main points of possible critique against the

model; is it reasonable that two pedestrians standing very close to each other affects a third pedestrian twice as much as if it was only one?

The *sFM* has, however, been extensively studied and proven to reproduce several well known features of pedestrian traffic, such as dynamic lane formation in opposing flows and oscillations at bottlenecks, as demonstrated already by Helbing and Molnár (1995), and dynamic stripe formation at intersecting flows (Helbing et al., 2005). It has also been successfully calibrated for different environments (A. Johansson et al., 2007; A. Johansson, 2009; Zanlungo et al., 2011), and adopted for simulation of evacuation scenarios, where the effects of panic is incorporated into the model (Helbing et al., 2000). This makes the *sFM* a very capable model, able to produce a wide range of behaviors using the same basic model.

Another advantage of the *sFM* is that it operates in continuous space, allowing detailed representation of the geometry of the environment, and avoiding the loss of accuracy associated with spatial discretization. The precision gained by the continuous space representation of course comes with a cost in terms of computational power required to run simulations; this is however a diminishing problem thanks to the development of faster computers.

The above are all good reasons to study the *sFM*, but there is another, almost as important reason that has nothing to do with the properties of the model: the *sFM* has been implemented in large commercial software for traffic simulation, and is being applied by practitioners planning future infrastructure. Thus, any new insights regarding properties of the *sFM*, or any improvements of it, may have immediate and important practical consequences.

3.1 Qualitative predictions of the *sFM*

The *sFM* builds on simple assumptions on the behavior of individual pedestrians and their interactions. The resulting behavior of a walker is the sum of its pairwise interactions with the other walkers. There is no mention of any macroscopic quantity in the model formulation; the *sFM* is a manifestly microscopic model. Naively, one would expect that a model of this type only would be able to correctly reproduce microscopic properties of the traffic, such as distance be-

tween pedestrians, and macroscopic properties directly derived from these, such as density. However, the SFM makes predictions of structures of the traffic at scales much larger than the scale at which the model operates. Here, *predictions* are used in the sense: the model correctly produces effects that have not been used in the formulation of the model. These predicted effects are often named *emergent phenomena*, since they emerge from the individual interactions, without being represented by any part of the model. The accurate predictions of well known emergent phenomena by the SFM is one of the main reasons for its credibility, and they will therefore be presented here.

When opposing pedestrian streams are dense enough, pedestrians start to organize into *dynamic lanes*; platoons of pedestrians with the same walking direction emerge, move through the traffic for a while, and then dissolve. The SFM predicts dynamic lane formation that seems to be similar to the observed phenomenon in real pedestrian traffic (Helbing and Molnár, 1995).

Dynamic lane formation can be seen as a special case of the more general phenomenon of *dynamic stripe* formation, appearing when two unidirectional flows intersect. In the intersection area stripes of pedestrians with common walking direction appears, also in this case if the density is high enough. The stripes are perpendicular to the bisector of the angle formed by the directions of the intersecting flows, and reduces to dynamic lanes in the case of opposing flows (Helbing et al., 2005).

Another prediction of the SFM, reported by Helbing and Molnár (1995), is oscillations in the direction of flow at bottlenecks of opposing flows. When the volume is high enough a jam will occur at the bottleneck with pedestrians on both sides trying to pass the bottleneck but being blocked by the other side. Soon, however, a pedestrian from one of the sides will break through and several other will follow after, in the wake of the first. The flow will soon stop and flow in the opposite direction follows, since there is now a smaller number of pedestrians blocking the bottleneck.

All these predictions of the SFM fits observations qualitatively; however, proper quantitative comparisons of the phenomena in the simulations to the observed are rare.

3.2 Structure of SFM based frameworks

The SFM is a model describing the spontaneous, or instinctive, interactions between pedestrians, as they try to walk with their preferred velocity without colliding with each other. There are, however, more to pedestrian behavior than what is described by the SFM. This section briefly describes the remaining components, beyond the SFM, needed to simulate pedestrian traffic, and discusses how these other components relates to the SFM.

A modeling framework for pedestrian behavior can be viewed as a three level structure of interacting models, where the levels correspond to different types of cognitive processes of the pedestrian. The three levels are often denoted the *strategical level*, corresponding to activity planning; the *tactical level*, corresponding to (dynamic) route choice; and the *operational level*, corresponding to evasive maneuvers. This division is motivated by the differences between the decision processes at each level, ranging from premeditated at the strategical level, to instinctive at the operational level, which motivates the usage of different types of behavioral models to describe the behavior on each level (Hoogendoorn and Bovy, 2004; Daamen, 2004). The structure of pedestrian behavior modeling frameworks are depicted in figure 3.1.

	Behavior	Spatial and temporal extension	Level of consciousness
Strategical	Activity planning	Global	Premeditated
Tactical	Route choice	Regional	Induced
Operational	Evasive maneuvers	Local	Instinctive

Figure 3.1: The structure of pedestrian models. In a SFM based framework the operational level is described by the SFM.

The model on the strategical level describes activity planning,

which is a relatively conscious, or premeditated behavior; we are aware of that we make a decision on what we should do and where and in what order we should do it. Pedestrians may reason about which alternative is the best and may have explicit preferences. The choices on the strategical level are usually made before the pedestrian arrives at the studied facility, and all the choices are dependent on each other. The perspective of the pedestrian is global, considering the whole trip, and the decisions are consistent: it is unusual that a pedestrian arrives by bike to a train station, wait until a train arrives, buys a bus ticket, and then walks to its car and drives away; some choices are only made in combination with other choices. The strategical level can often be described as a choice between a finite number of alternatives, where the personal preferences and needs of the pedestrians are important for the choice. Discrete choice theory is a possible approach to model the strategical level. Also the choice to visit or not to visit the facility may be included on the strategical level. Alternatively the demand, that is the number of visiting pedestrians, can be seen as input to the strategical level.

The tactical level corresponds to the route choice of the pedestrians, that is, what route to take between the activities planned at the strategical level. Exactly how a route is specified may differ between different models, but generally a route is, roughly, an ordered sequence of sub-areas of the total walkable area. The decisions on tactical level may depend on the perceived conditions at different parts of the facility.

The route choice models may be divided into three different categories; namely those which are

1. independent of the traffic volumes, for example shortest route or walking as much as possible indoors;
2. static, depending only on the average or typical traffic conditions; or
3. dynamic, corresponding to pedestrians that re-plan their route if they encounter congestion on their planned route.

The model at the tactical level of the framework takes as input the activity plan resulting from the strategical level and produces a route for the walker to follow.

In a SFM based framework, the route choice model must result in a specification of the preferred velocity of each walker at each point in space and time, since this is the necessary input to the SFM that encodes the preferred movement of the walker. The preferred velocity must be specified on the whole walkable area, and not just along the planned path, since the walker may end up anywhere due to interactions with other walkers. In the simple case of shortest path route choice, the output of the route choice model is a vector field specifying the preferred velocity of the walker at every point of the walkable area, such that its integral curves describes the shortest walkable paths to the destination from each point in the walkable area.

Apart from route choice also the choice of preferred speed and re-planning of activities may be included at the tactical level. An example of behavior modeled at the tactical level is re-planning of route and preferred speed due to a broken elevator.

The operational level corresponds to the instinctive decisions that pedestrians make to keep their distance to other pedestrians, while trying to follow the route decided at the tactical level. Pedestrians are seldom aware of these decisions, and the decisions are even less frequently thought through. The process of navigating through a crowd while avoiding collisions is obviously largely automated, and also functions well; collisions are very rare, even though pedestrians do not actively think about how they should act to avoid them. This suggests that if we can find a simple stimulus – response mechanism that can produce collision free pedestrian traffic, it may be sufficient as a model of the operational level. The SFM is such a mechanism, taking the preferred velocity of each walker at each point in the walkable area as input from the tactical level, and produces the operational behavior, consisting mainly of evasive maneuvers. Thus the preferred velocity is external to the SFM; any behavioral model that determines the preferred velocity of the walkers operates at the tactical level.

3.3 Specifications of the SFM

The SFM was proposed by Helbing and Molnár (1995). Although some steps toward it had been taken previously in Helbing (1991) and Helbing (1993), the first model lacks the simplicity of the model proposed in Helbing and Molnár (1995), and the work in Helbing

(1993) is focused on describing general social dynamics using equations similar to the Boltzmann equation from statistical physics.

The forces introduced by Helbing and Molnár (1995) are of four types: the *preferred force* describing the desire of the pedestrian to walk with its preferred velocity; the *interaction force* between walkers, keeping them from colliding; the *obstacle force*, keeping walkers from colliding with walls and other obstacles; and finally *attraction forces* that are claimed to be useful to simulate groups of pedestrians keeping together or to simulate attractions of various kinds. However, no details or simulation results including the last type of forces are given, so this type will be ignored here.

3.3.1 The preferred force

Each walker, i , is, at each moment of time and at each position, assumed to have a *preferred velocity*, $\mathbf{v}_i^p$, describing how the walker would prefer to move in the absence of other walkers. The preferred speed differs of course significantly between pedestrians. Helbing and Molnár (1995) use a Gaussian distribution $v_i^p \sim \mathcal{N}(\mu, \sigma^2)$, with mean $\mu = 1.34 \text{ m s}^{-1}$ and standard deviation $\sigma = 0.26 \text{ m s}^{-1}$ to describe the differences in preferred speed between pedestrians, and refer to Weidmann (1992). Helbing et al. (2005) claim, that under normal conditions, $v_i^p \sim \mathcal{N}(\mu, \sigma^2)$, $\mu = 1.3 \text{ m s}^{-1}$ and $\sigma = 0.3 \text{ m s}^{-1}$ is a suitable choice. However, in an empirical study, Henderson and Lyons (1972) found an actual speed distribution with a mean of around 1.5 m s^{-1} , and significant differences between female and male pedestrians, indicating that using one Gaussian distribution for the whole population at a location may be an oversimplification.

Helbing et al. (2005) discuss a dynamic choice of the preferred speed, where delays induce increased preferred speed. Pedestrians are assumed to prefer to walk at a speed such that they reach their destination at a certain time, and thus increases the speed if delayed to still be able to reach the destination in time.

The preferred force of walker i describes the desire of the walker to approach its preferred velocity if its current velocity differs from it, and is defined as

$$\mathbf{F}_i^p = \frac{1}{\tau} (\mathbf{v}_i^p - \dot{\mathbf{x}}_i), \quad (3.1)$$

where $\mathbf{x}_i$ is the position of walker and τ is a model parameter describing how quickly the walker adapts to its preferred velocity. The parameter τ also determines the aggressiveness of a walker, the lower the value of τ , for a given preferred speed, the stronger the force needed to make it slow down and stop. Thus, a walker with a low value of τ exhibits a pushy behavior, that is, cares less that other walkers are in its way. However, τ is often assumed constant over the population. Here, and in the following, the quantities' dependences on time and the position of the walker have been suppressed for clarity.

The assumptions behind equation (3.1) can be made more clear by interpreting the two terms on the right hand side as, in physical terms, the constant force attracting the walker to the destination and the velocity dependent friction experienced when moving, respectively. The force dragging the walker toward its destination represents the desire of the walker to reach its destination as quickly as possible, while the friction represents the cost, or aversion against, moving quickly. Assuming that the strength of the force toward the destination is constant, and that the aversion against moving at a certain speed is proportional to the speed, gives equation (3.1). The preferred velocity is then the velocity at which these two forces are at equilibrium.

This form of the force is used in almost all microscopic continuous space models, with a notable exception in the model of Hoogendoorn and Bovy (2002), in which the preferred force is represented by the first term on the right hand side of equation (2.9), which also corrects for the spatial variation of the preferred velocity field. The omission of this correction factor in equation (3.1) implies that in cases where the direction of the preferred velocity field varies, walkers do not include the fact that they soon will prefer to walk in another direction into their behavior. Thus, the path of a *free walker*, that is, a walker that is not affected by any forces except its preferred force, does not coincide with one of the integral curves of the preferred velocity field.

A free walker moves according to the equations of motion

$$\ddot{\mathbf{x}}_i = \frac{1}{\tau} (\mathbf{v}_i^p - \dot{\mathbf{x}}_i). \quad (3.2)$$

Note that if we can observe pedestrians that accelerate up to their preferred speed, for example after stopping for a traffic light, and if

they can be assumed to be free, we can directly observe the distribution of both v_i^p and τ over the population. Such an experiment was reported by Ma et al. (2010), who found a preferred speed distribution with mean 1.51 m s^{-1} and standard deviation 0.15 m s^{-1} , and a distribution of τ with a mean of 0.71 s and a standard deviation of 0.1 s . It should, however, be noted that this study was performed as a controlled experiment, with pedestrians being told what to do. A similar controlled experiment was made by Moussaïd et al. (2009), with the results $v_i^p = 1.29 \pm 0.19 \text{ m s}^{-1}$, and $\tau = 0.54 \pm 0.05 \text{ s}$. A. Johansson (2009), and Zanlungo et al. (2011) using different genetic algorithms to calibrate the model obtained $\tau \approx 0.6 \text{ s}$ and $\tau \approx 1.19 \text{ s}$, respectively.

Although there are some variations, τ is generally assumed to be constant over the population. Helbing and Molnár (1995) assume that a value $\tau = 0.5 \text{ s}$ is suitable, while Helbing et al. (2005) assume $\tau \approx 1 \text{ s}$.

If we solve equation (3.2) for the velocity of the walker, assuming a constant preferred velocity, we get

$$\dot{\mathbf{x}}_i(t) = (\dot{\mathbf{x}}_i(0) - \mathbf{v}_i^p) e^{-t/\tau} + \mathbf{v}_i^p, \quad (3.3)$$

that is, a free walker approaches its preferred velocity exponentially in time. This exponential acceleration process was experimentally confirmed by Moussaïd et al. (2009) and Ma et al. (2010).

3.3.2 The interaction force

The interaction force that models the desire to avoid collisions and to stay at a comfortable distance from other pedestrians is given by a potential of the form

$$V_{ij} = F_0 \sigma e^{-b/\sigma}, \quad (3.4)$$

where F_0 and σ are model parameters giving the magnitude and range scale of the force respectively, and the function $b = b(\mathbf{x}_i, \mathbf{x}_j, \dot{\mathbf{x}}_i, \dot{\mathbf{x}}_j)$ describes the shape of the potential. The interaction force is given by the negative of the gradient of the potential,

$$\mathbf{F}_{ij} = -\nabla V_{ij}, \quad (3.5)$$

where the gradient is taken with respect to the space coordinates.

In the original work, by Helbing and Molnár (1995), the shape of the potential was proposed to be given by

$$b = \frac{1}{2} \sqrt{(r_{ij} + |\mathbf{r}_{ij} - \dot{\mathbf{x}}_j T_s|)^2 - (\dot{x}_j T_s)^2}, \quad (3.6)$$

where $\mathbf{r}_{ij} = \mathbf{x}_i - \mathbf{x}_j$ is the position of the affected walker i , relative to the affecting walker j . The model parameter T_s was assumed to be in the order of the time it takes a pedestrian to take one step, which is reported to be around 0.5 s (Hoogendoorn et al., 2003). However, the interpretation that T_s is in the order of a step time was dropped immediately by Helbing and Molnár (1995); in their simulations the value $T_s = 2$ s is used, which would give a step length of 2.7 m for normal free flow speeds.

The shape of the potential specified through equation (3.6), is that of an ellipse directed in the direction of motion of the walker, as depicted in figure 3.2. This shape was motivated by the assumption that the affected pedestrian give room for the affecting pedestrian to take its next step.

Figure 3.2: The potential V_{ij} , equation (3.4), with b according to equation (3.6). The affecting walker, represented by the triangle, is located at the origin and is moving at 1.3 m s^{-1} in the positive x -direction. The parameters used are $F_0 = 7 \text{ m s}^{-2}$, $\sigma = 0.3$, and $T_s = 2 \text{ s}$, as in Helbing and Molnár (1995).

This and two other versions of the interaction force were investigated by A. Johansson et al. (2007) and A. Johansson (2009). One of these alternative versions was the special case of equation (3.6) when $T_s = 0$. This results in a rotationally symmetric circular specification,

$$b = r_{ij}. \quad (3.7)$$

When this, much simpler, model was calibrated the fit to the observations was surprisingly good, actually very close to the elliptical specification (A. Johansson et al., 2007). This implies that the significantly less computationally demanding circular specification can be used as a good approximation to equation (3.6).

A. Johansson et al. (2007) also proposed and investigated a third version of the potential, obtained by replacing the velocity of the affecting walker, $\dot{\mathbf{x}}_j$, with the velocity of the affecting walker relative to the affected one, $-\dot{\mathbf{r}}_{ij} = \dot{\mathbf{x}}_j - \dot{\mathbf{x}}_i$. This results in the shape

$$b = \frac{1}{2} \sqrt{(r_{ij} + |\mathbf{r}_{ij} + \dot{\mathbf{r}}_{ij} T_s|)^2 - (\dot{r}_{ij} T_s)^2}. \quad (3.8)$$

This specification suggests a slightly different interpretation of the elongation of the potential. Instead of just being due to respect for the affecting pedestrians' next step, it becomes a more general model of the anticipatory behavior of the pedestrians. The affected walker interpolate linearly the relative position of the affecting walker at time $t + T_s$, and avoid this position equally strongly as the actual position at time t . Note also that the potential in this specification is symmetric with respect to permutation of indexes, $i \leftrightarrow j$. This property implies that the force is antisymmetric in the indexes, which can be utilized to speed up the computation of the forces during simulation.

The forces resulting from each of the above specifications can be explicitly calculated, giving for the first elliptic specification, equation (3.6),

$$\mathbf{F}_{ij} = \frac{(r_{ij} + |\mathbf{r}_{ij} - \dot{\mathbf{x}}_j T_s|)}{4b} \left(\frac{\mathbf{r}_{ij}}{r_{ij}} + \frac{\mathbf{r}_{ij} - \dot{\mathbf{x}}_j T_s}{|\mathbf{r}_{ij} - \dot{\mathbf{x}}_j T_s|} \right) F_0 e^{-b/\sigma}, \quad (3.9)$$

and for the second elliptical specification, equation (3.8),

$$\mathbf{F}_{ij} = \frac{(r_{ij} + |\mathbf{r}_{ij} - \dot{\mathbf{r}}_{ij} T_s|)}{4b} \left(\frac{\mathbf{r}_{ij}}{r_{ij}} + \frac{\mathbf{r}_{ij} - \dot{\mathbf{r}}_{ij} T_s}{|\mathbf{r}_{ij} - \dot{\mathbf{r}}_{ij} T_s|} \right) F_0 e^{-b/\sigma}, \quad (3.10)$$

and finally for the rotationally symmetric specification, equation (3.7),

$$\mathbf{F}_{ij} = \frac{\mathbf{r}_{ij}}{r_{ij}} F_0 e^{-r_{ij}/\sigma}. \quad (3.11)$$

Yet another version of the interaction force was proposed by Zanolungo et al. (2011). Instead of elongating the potential to model the anticipatory behavior of the pedestrians, their model explicitly calculates, for each pair of walkers, the future time at which the pair is separated by the minimum distance, given that they keep their current velocities. This time, and the location of the walkers at this time, are then used to calculate an interaction force. The model is reminiscent of a game theory based model, where the tactic of the opponent is assumed to be to do nothing, that is, keep the current velocity.

Zanolungo et al. (2011) calibrated their model and the previous three¹, using the same calibration method for all models. This resulted in best performance for the new model. However, all models were modified by adding an elastic core to the walkers, and collisions of the elastic cores were punished in the fit measure of the calibration procedure. Thus, using such measure, the good performance of the model that explicitly calculates future collisions, can be expected.

Pedestrians have a limited field of view, thus walkers should be less affected by objects behind them than in front of them. In the original work (Helbing and Molnár, 1995) this was achieved through the introduction of direction dependent weights,

$$w(\mathbf{e}_i, \mathbf{F}) = \begin{cases} 1, & \text{if } \mathbf{e}_i \cdot \mathbf{F} \geq F \cos \phi, \\ c, & \text{otherwise,} \end{cases} \quad (3.12)$$

for any force $\mathbf{F}$, where ϕ is half the field of view angle, $c \in (0, 1)$ is a model parameter, and $\mathbf{e}_i$ is the looking direction of the walker, assumed to be the same as the direction of the preferred velocity,

$$\mathbf{e}_i = \frac{\mathbf{v}_i^p}{v_i^p}. \quad (3.13)$$

A disadvantage of this specification of the weights is that a walker would experience a discontinuity in the force affecting it when a walker enters its field of view. This may at first seem realistic, but since the

¹and yet another model, by Shukla (2010)

head and eye movements of the walker is not modeled at all, the field of view of the walker should be interpreted as an effective field of view, including head and eye movements, and thus there should be no sharp limit where an object enters the field of view.

These anisotropic weights were later generalized by Helbing et al. (2002) to

$$w(\mathbf{e}_i, \varphi_{ij}) = \lambda + (1 - \lambda) \frac{1 + \cos \varphi_{ij}}{2}, \quad (3.14)$$

where $\lambda \in [0, 1]$ is a model parameter and φ_{ij} is the angle between the looking direction of the affected walker and the direction to the affecting walker, that is, $r_{ij} \cos \varphi_{ij} = -\mathbf{r}_{ij} \cdot \mathbf{e}_i$. Using this specification of the anisotropic weights with $\lambda = 0$ implies that a walker is fully affected by the presence of another walker only if it is located in the looking direction of the walker, and a walker is not affected at all by a walker located exactly behind it. Setting $\lambda = 1$ implies that the looking direction of a walker is irrelevant.

3.3.3 Other forces

The obstacle force exerted by obstacle n on walker i is similar to the interaction force and ensures that walkers do not collide with walls and other obstacles,

$$\mathbf{F}_{in}^{\text{OBST}} = F_0^{\text{OBST}} \frac{\mathbf{r}_{in}}{r_{in}} e^{-r_{in}/\sigma^{\text{OBST}}}, \quad (3.15)$$

where F_0^{OBST} and σ^{OBST} are model parameters, analogous to F_0 and b , and $\mathbf{r}_{in}$ is the position of the walker relative to the point closest to it on the obstacle. The values of the parameters are by Helbing and Molnár (1995) assumed to be $F_0^{\text{OBST}} = 50 \text{ m s}^{-2}$ and $\sigma^{\text{OBST}} = 0.2 \text{ m}$, and by Moussaïd et al. (2009) to be $F_0^{\text{OBST}} = 3 \text{ m s}^{-2}$ and $\sigma^{\text{OBST}} = 0.1 \text{ m}$. Note the huge difference between these two pairs of parameter values.

In addition to these four categories of forces Helbing and Molnár (1995) also include a random force term, $\mathbf{F}^{\text{RAND}}$, to include mistakes and other deviations from the usual behavior.

To be able to simulate the extreme pedestrian densities that may occur during evacuation of panicking crowds Helbing et al. (2000) extended the model. At high densities the size of the human body becomes important. Also, under such conditions people are less inclined to respect the movement of other people, so the rotationally

symmetric specification, equation (3.7), of the repulsive potential is used. In the original model, however, walkers could be arbitrarily close to each other since the model does not include any element representing the body of the pedestrian; the walkers were effectively point particles. Helbing et al. (2000) introduce a body size in the model by replacing r_{ij} with $r_{ij} - R_{ij}$, where $R_{ij} = R_i + R_j$, is the sum of the radii of the interacting walkers. The radii were assumed to vary over the population, $R_i \sim \mathcal{U}(0.25 \text{ m}, 0.35 \text{ m})$. In addition to the above mentioned *social* forces, they introduce *physical* forces, $\mathbf{F}_{ij}^{\text{PHYS}}$, acting only when pedestrians touch, that is, when $r_{ij} < R_{ij}$. The added forces were a *body force*, describing the repulsive force resulting from an elastic compression of the body; and a *friction force*, describing the tangential friction between two touching bodies.

The panic model was also discussed by Helbing et al. (2002), and modifications to it was proposed by Lakoba et al. (2005). Helbing et al. (2005) use a body force of the same form as the circular specification of the interaction force, equation (3.11), not affected by the anisotropic weights, and an interaction force of the same shape, but affected by the weights. Yu and A. Johansson (2007) investigated another way of including a body force to investigate the phenomenon of crowd turbulence that may occur at extreme pedestrian densities. Instead of including the body force as a separate term they modeled the effect using an additional term in the exponent of the interaction force. For this to be realistic of course it is required that the anisotropy of the interaction force is not too strong.

3.3.4 Equations of motion

All the social forces are assumed to affect the walker simultaneously and independently, resulting in a desire of the walker to accelerate in the direction of the resultant of the forces,

$$\mathbf{a}_i = \mathbf{F}_i^{\text{P}} + \sum_j \left(w(\varphi_{ij}) \mathbf{F}_{ij} + \mathbf{F}_{ij}^{\text{PHYS}} \right) + \sum_n \mathbf{F}_{in}^{\text{OBST}} + \mathbf{F}^{\text{RAND}}. \quad (3.16)$$

This is the acceleration the walker *tries* to apply, its speed is however bounded by v_i^{MAX} , so the equations governing the motion of the

walker becomes

$$\dot{\mathbf{v}}_i = \mathbf{a}_i, \quad (3.17a)$$

$$\dot{\mathbf{x}}_i = \frac{\mathbf{v}_i}{v_i} \min \left\{ v_i, v_i^{\text{MAX}} \right\}. \quad (3.17b)$$

Here, $\mathbf{v}_i$ is not the actual velocity of the walker, but the velocity that the walker tries to walk at; the actual velocity of the walker is $\dot{\mathbf{x}}_i$. An upper bound on the speed of walkers is clearly needed for a realistic model. However, this way of introducing such upper bound introduces some nontrivial effects in some rare situations. If a walker is pushed from behind for a prolonged period of time, typically by several much faster walkers, even though it is already walking at its maximum speed it will according to equation (3.17a) *try* to walk faster and faster. When the force from behind finally disappears the walker will be affected by a decelerating preferred force, equation (3.1) with $\dot{\mathbf{x}}_i > v_i^p$. But according to equation (3.17b) the walker will not start to slow down until v_i has been reduced to below v_i^{MAX} . Thus, according to the SFM, pedestrians may get stressed by surrounding pedestrians causing her or him to walk quicker than when alone. Further this effects lingers some time after the cause of the stress has disappeared.

Parisi et al. (2009) note that walkers simulated using the SFM tend to push slower walkers out of their way. Since such behavior is limited in normal conditions they propose a modification that sets the preferred speed of a pedestrian to zero, temporarily, if there is insufficient space available in front of it. They find an increased fit to observational data if their method is used. Note, however, that this modification is not strictly a modification of the SFM, since the preferred velocity is external to the model. It may be desirable to model the instinctive behavior of avoiding pushy behavior on the operational level.

Chapter 4

Modeling waiting pedestrians

ALMOST in every scenario with pedestrian traffic there are occurrences of waiting pedestrians. People wait for their friends, for their bus or train to arrive, or for the traffic signal to switch to green. But they can also stand still for other reasons, such as reading an information sign to see when their tram arrives, or looking at a shop window or a street artist. In all of the above situations the pedestrian have no desire to move, so if nobody else is around the pedestrian will simply stay at the same place until it is finished with the activity. We will call this behavior waiting. But what will the waiting pedestrian do if someone passes by? Will she or he move out of the way or stay fixed at one spot? What if a group of people passes by, or a whole buss load? What if there is an almost constant flow of people walking by? How much will the waiting person move, if at all?

These questions may seem to be of marginal importance, but in situations where there are many waiting pedestrians standing in the way of pedestrians in a hurry, the behavior of the waiting pedestrians may have a large influence on how quickly the hurried pedestrians can pass the waiting group. Anyone who has tried to pass through a crowded railway station on their way to a train about to leave can appreciate the importance of delay inflicted by the waiting crowd.

The hypothesis of the research presented in this chapter is that accurate models of waiting pedestrians is important. When a scenario containing sufficiently many waiting pedestrians is simulated to obtain travel times and other measures of the Quality of Service (QoS), the model that is used to describe the behavior of waiting pedestrians may have a significant effect on the result. The purpose of the research presented in this chapter is to investigate *how* important the choice of waiting model is for the results of simulations of pedestrian traffic.

In section 4.1 we conclude that this question is not answered by the existing literature on pedestrian simulation in general, and the question has not been considered within a SFM based modeling framework. Furthermore, no extensions of the SFM to include waiting pedestrians have been proposed, so estimating the influence of such model extensions on the results of simulations is not possible without first developing the extensions. In sections 4.3 to 4.5, we propose a sequence of three extensions to the SFM to model waiting pedestrians. Then, in section 4.6, we compare the results of these three models to estimate how important the inclusion of waiting walkers into a simulation model is, and to estimate the sensitivity of the result to the choice of waiting model. In other words, we estimate the importance of choosing the correct model.

4.1 Previous work on waiting pedestrians

The problem of modeling waiting pedestrians has received surprisingly little attention in the academic literature. The only reference found on how to simulate waiting pedestrians was a recent article by Davidich et al. (2013). In the article, the authors both present an observational study of waiting behavior on two German railway stations, and propose a CA based model of waiting pedestrians. As soon as a walker enters its predefined destination waiting zone, a random cell within the zone is chosen as waiting position. Since the model is based on CA, the waiting walker is simply fixed in one cell for the whole duration of its waiting activity, and do not react in any way to the surrounding traffic. The authors argue that this lack of reaction is not an oversimplification at railway stations, since a large fraction of the population have luggage and therefore do not move.

Using this model, the authors show that the effect on the mean delay of including waiting walkers in the simulation of a railway platform is as large as 20 % increase compared to the case without any waiting walkers, thus proving the importance of including waiting walkers in simulations. The input data for the simulation: number of waiting and alighting pedestrians, velocity distribution etc., as well as the physical design of the platform, was collected at the observed railway stations. This guarantees that the data is realistic, but also makes the results specific for the studied situation.

The work by Davidich et al. (2013) is important in that it indicates the *potential* importance of including waiting walkers in simulations, assuming that waiting walkers do not react at all to the surrounding traffic. This assumption implies that the model may overestimate the delay that waiting pedestrians incur on the passing traffic, since real waiting pedestrians may in fact adjust their position as a result of the passing traffic, thereby reducing the incurred delay. Furthermore, the CA nature of the model implies that a row of waiting walkers standing in neighboring cells constitute an impermeable wall, which may contribute to the delay.

4.2 New models of waiting pedestrians

In the following sections a series of model extensions to the SFM are presented. The first of the proposed models is the simplest possible model of waiting pedestrians in a SFM based framework. In this model we assign a vanishing preferred velocity to waiting walkers. This model may, due to its extreme simplicity, not be applicable to some situations. Thus, the second, slightly more advanced model is constructed based on a different assumption of the behavior of waiting pedestrians. Here we assign a preferred position to a waiting walker and set the preferred velocity directed toward this position. Also this model is constructed with simplicity as guideline, and has another, but still limited area of applicability. Finally the third model is constructed as a generalization of the second model, allowing for greater flexibility in the behavior of the waiting walkers. In this model the walker dynamically adapts its preferred position based on the traffic conditions.

In contrast to the model proposed by Davidich et al. (2013), the

proposed models are continuous in space and the waiting pedestrians react to the surrounding traffic; this will result in a more conservative estimate of the impact of waiting pedestrians on the passing traffic, since the waiting walkers will be "helpful" and move slightly out of the way of the passing walkers. This conservative stance is achieved by letting the waiting walkers behave according to the sfm with minimal modifications.

Since it is unreasonable to assume that waiting walkers would react more strongly to passing traffic than non-waiting walkers, the chosen strategy, to let them react according to the same model, is likely to produce conservative predictions of the delay of the passing traffic caused by a waiting crowd. If the proposed models predict delays that are significant from an application perspective, we have shown that the inclusion of waiting walkers in simulation models of pedestrian traffic is important.

For a simulation framework to be a useful tool to simulate pedestrian traffic containing waiting pedestrians it should contain both walking and waiting walkers, and allow for a transition between the two. A walking walker should be able to become a waiting walker and vice versa. Since different behavioral models will control the two types of walkers we introduce *Activities*. Which activity a walker is engaged in determines which model it obeys: the walking model or the waiting model. The term *walker* will in this chapter be reduced to only denote walking walkers, while the term *waiter* will be used for waiting walkers.

We let the transition from walking to waiting be controlled by the location of the walker; a walker becomes a waiter when it reaches a predetermined waiting area. This transition rule is of course only a special case of a large number of possible realistic rules that should be chosen in accordance with the simulated scenario.

The choice to wait is a conscious decision, so there should be some difference between the models for the behaviors of walking and waiting walkers at the tactical level of the modeling framework. In the sfm the desire of a walker is to reach its destination as quickly as possible subject to its limited walking speed. This desire is controlled at the tactical level of the modeling framework by setting the preferred velocity of the walker to be directed along the shortest path from the position of the walker to its destination. Note also that the preferred

velocity of a walker is *necessary* input to the sFM; it must be defined. The desire of a waiter, and thus its preferred velocity, must clearly be something different than for a walker, since a waiter does not have a destination that it would like to reach as quickly as possible. Thus, the modeling of waiting pedestrians in a sFM based simulation framework must include the choice of the preferred velocity for the waiters, otherwise it is not possible to use the sFM for the operational behavior of the waiters.

From the above discussion a general conclusion regarding this type of waiting models can be drawn. In the absence of surrounding traffic, a waiter must, if it remains waiting for a sufficient time, reach a state in which it is stationary and has a vanishing preferred velocity. This means that any waiting model based on the manipulation of the preferred velocity must be able to handle a vanishing preferred velocity. This is not the case for the common version of the sFM described in chapter 3 since the looking direction is defined to be in the direction of the preferred velocity, according to equation (3.13). Thus, any waiting model of this type must extend the sFM by prescribing a looking direction while waiting.

All the waiting models proposed in the following sections will have a common definition of the looking direction while waiting, $\mathbf{e}^w$. We assume that there is an object of interest, for example an information sign or shopping window, which the walker will look at during the waiting activity. We call the location of this object of interest the focus point, and denote it $\mathbf{x}^F$. The focus point can in principle be individually chosen for each walker, and can also depend on time, but we will in the following assume that there only is one stationary focus point for each waiting area ω . Thus, the looking direction of a waiter is

$$\mathbf{e}^w = \frac{\mathbf{x}^F - \mathbf{x}}{|\mathbf{x}^F - \mathbf{x}|}. \quad (4.1)$$

Here, and in the rest of this chapter, the index i , enumerating the walkers will be dropped, since only one walker at a time will be considered in the equations. The geometry of the focus point and looking direction is summarized in figure 4.1.

Figure 4.1: The geometry of the looking direction and the focus point. The looking direction $\mathbf{e}^w$ is always directed toward the focus point, $\mathbf{x}^F$, for a waiter. The looking direction will be omitted in the following figures and only indicated by the orientation of the triangle representing the waiter. The velocity of the waiter, $\dot{\mathbf{x}}$, is arbitrarily chosen in this and the following figures.

4.3 The preferred velocity model

The simplest possible choice of the preferred velocity that can result in a realistic waiting behavior is to simply set the preferred velocity while waiting to zero, $\mathbf{v}^{\text{pw}} = \mathbf{0}$. We call this model the Preferred Velocity Model (pvm). Since the preferred velocity vanishes, the preferred force, equation (3.1), is reduced to

$$\mathbf{F}^{\text{pw}} = -\frac{\dot{\mathbf{x}}}{\tau} \quad (4.2)$$

for a waiter. The geometry of the pvm is indicated in figure 4.2.

Thus a waiter obeying this model has the desire to slow down and stop, regardless of where it is or what is happening. While having this aim, it still obeys the sfm and performs evasive maneuvers to avoid close encounters with other waiters or walkers.

If a pvm controlled waiter for some reason is not at rest; it may be that it recently has avoided a passing walker, or that it has recently entered the waiting area; but is currently unaffected by any external forces, it will move according to the differential equations

$$\ddot{\mathbf{x}} = \frac{\dot{\mathbf{x}}}{\tau}, \quad (4.3)$$

Figure 4.2: The geometry of the PVM. The preferred force while waiting, $\mathbf{F}^{\text{PW}}$, is anti parallel to the velocity, $\dot{\mathbf{x}}$.

which results in an exponentially decreasing speed. Let $\dot{x}(t = 0) = v_0$, then the waiter will stop within a distance

$$s = \int_0^{\infty} \dot{x} dt = v_0 \tau. \quad (4.4)$$

A typical pedestrian has a preferred velocity of around 1.34 m s^{-1} and calibration by different groups indicate that τ vary between $\tau \approx 0.6 \text{ s}$ and $\tau \approx 1.19 \text{ s}$. This means that a typical waiter will stop within between $s \approx 0.8 \text{ m}$ and $s \approx 1.6 \text{ m}$ of the point at which it entered the waiting area.

The PVM has a feature that is certainly not suitable in all situations: since the waiters obey the SFM, they will react to any passing traffic by moving slightly away from the passing walker and then stop, slightly displaced from its previous position. Even a sparse flow of passing pedestrians may result in a significant drift of the waiters away from the passing traffic. This drifting behavior may be observed in some situations, but certainly not in general. In the next section, we introduce an alternative model extension that includes a desire of the waiters to remain at one place, instead of accepting any spot they happen to stop at as an acceptable waiting position.

4.4 The preferred position model

If we make the assumption that a waiter has a point at which it prefers to stand while waiting the above mentioned drifting can be avoided. We call the resulting model the Preferred Position Model (PPM).

Assume that a waiter has a *preferred waiting position*, $\mathbf{x}^{\text{PW}} \in \omega$, which it at all times strives to stand at. Encoding this desire into the model corresponds to setting the direction of the preferred velocity of the waiter toward its preferred position. Furthermore it is reasonable to assume that the desire of the walker to move toward its preferred position decreases as it gets closer to it, and that this decrease is continuous. This translates directly to the preferred speed; it should decrease as the distance to the preferred position decreases. Of course the preferred speed should vanish at the preferred position, and be equal to the regular preferred speed, v^p , when the walker is far from the preferred position.

We keep to the guiding principle of model simplicity and let the preferred speed depend linearly on the distance to the preferred position, and obtain the following specification of the preferred velocity,

$$\mathbf{v}^{\text{PW}}(\mathbf{x}) = \begin{cases} v^p(\mathbf{x}^{\text{PW}} - \mathbf{x})/d, & |\mathbf{x}^{\text{PW}} - \mathbf{x}| \leq d, \\ v^p(\mathbf{x}^{\text{PW}} - \mathbf{x})/|\mathbf{x}^{\text{PW}} - \mathbf{x}|, & |\mathbf{x}^{\text{PW}} - \mathbf{x}| > d. \end{cases} \quad (4.5)$$

Here, d is a model parameter determining the the distance from the preferred position at which the waiter obtains its regular preferred speed, and thus also the rate at which the preferred speed increases as the distance to the preferred position increases. The geometry of the PPM is described in figure 4.3.

We will now consider the effect of the value of the parameter d on the properties of the model. We do this by considering the equation of motion of a free waiter within the distance d of its preferred position, given by inserting the preferred velocity in equation (4.5) into equation (3.2),

$$\ddot{\mathbf{x}} + \frac{1}{\tau}\dot{\mathbf{x}} + \frac{v^p}{\tau d}\mathbf{x} = \mathbf{0}, \quad (4.6)$$

if the coordinates are chosen such that the preferred position is at the origin. Each of these two ordinary differential equations, one for each coordinate of the position of the waiter, is the equation of a damped harmonic oscillator, with damping coefficient $\zeta = \sqrt{d/4v^p\tau}$.

Figure 4.3: The geometry of the PPM. The preferred velocity while waiting, $\mathbf{v}^{\text{PW}}$, is directed toward the preferred position, $\mathbf{x}^{\text{PW}}$, and has a magnitude proportional to the distance to $\mathbf{x}$ within the circle of radius d .

A damped harmonic oscillator is a well known physical system, and may have three different types of behavior, depending on the value of ζ . If $\zeta > 1$ the system is called over damped and will quickly return to its equilibrium state, in our case the preferred position, without passing it. This motion will be slower for higher values of ζ . If $\zeta < 1$ the system is called under damped, and will oscillate around its equilibrium state, with decreasing amplitude. Finally, in the limiting case when $\zeta = 1$ the system is called critically damped and will return as quickly as possible to the equilibrium state, without starting to oscillate.

Oscillatory behavior is definitely not desirable, so $\zeta \geq 1$. Since the general behavior of SFM walkers is to try to get to their destination as quickly as possible, it seems reasonable to demand that here as well, which gives,

$$1 = \zeta = \sqrt{d/4v^p\tau} \Rightarrow d = 4v^p\tau. \quad (4.7)$$

Thus, we have arrived at a waiting model without any new free parameters,

$$\mathbf{v}^{\text{PW}}(\mathbf{x}) = \begin{cases} (\mathbf{x}^{\text{PW}} - \mathbf{x})/4\tau, & |\mathbf{x}^{\text{PW}} - \mathbf{x}| \leq 4v^p\tau, \\ v^p(\mathbf{x}^{\text{PW}} - \mathbf{x})/|\mathbf{x}^{\text{PW}} - \mathbf{x}|, & |\mathbf{x}^{\text{PW}} - \mathbf{x}| > 4v^p\tau, \end{cases} \quad (4.8)$$

and looking direction according to equation (4.1).

The PPM produces the desired behavior, that is, a waiter reacts to passing walkers, but then returns to the preferred position, and the drifting is removed. This model, however, introduces another behavior that may be unrealistic in some situations. The waiter always returns to its preferred position, no matter how many times it gets disturbed by passing walkers. In many situations one would expect the waiter to modify its preferred position if the first choice has turned out to be unattainable. For example, if the preferred position was located in the middle of a continuous flow of walkers, instead of trying to go back as soon as a gap in the passing traffic appeared, one would in many situations expect a walker to adjust its preferred position such that it would not interfere too much with the passing traffic.

4.5 The adapting preferred position model

To construct the Adapting Preferred Position Model (APPM), in which the preferred position is adapted to the traffic conditions, we include the preferred position as a dynamical entity in the model. Let the preferred position be modeled as a particle with mass M , and let it be affected by a force of equal magnitude, but opposite direction, as the preferred force, $\mathbf{F}^p$, acting on the waiter. In this way, a pair of waiter and preferred position obeys Newton's law of action and reaction, which simplifies the model. In this sense this choice of force is the simplest possible. To stabilize the system, we also introduce a friction force, $-k\dot{\mathbf{x}}^{pw}$, where k is a new model parameter.

Normally in a SFM context, the mass of a walker is set to 1, or equivalently, units are chosen such that the mass of a walker is 1, that is we measure all masses in units of "walker masses". When discussing the APPM however, we will explicitly include the mass of the waiter, m , since we in this context also have the mass of the preferred position present. This will, hopefully, clarify equations by simplifying dimensional analysis.

The motion of an APPM waiter and its preferred position is deter-

mined by

$$\mathbf{F}^{\text{PW}} = \frac{m}{\tau} (\mathbf{v}^{\text{PW}}(\mathbf{x}) - \dot{\mathbf{x}}), \quad (4.9a)$$

$$M\ddot{\mathbf{x}}^{\text{PW}} = -\mathbf{F}^{\text{PW}} - k\dot{\mathbf{x}}^{\text{PW}}, \quad (4.9b)$$

with $\mathbf{v}^{\text{PW}}$ according to the same principle as for the PPM, equation (4.5). The geometry of the APPM is depicted in figure 4.4. Note that the velocity of the waiter still is limited by equation (3.17b).

Figure 4.4: The geometry of the APPM. The velocity of the preferred position, $\dot{\mathbf{x}}^{\text{PW}}$, is arbitrarily chosen in the figure. The preferred position is affected by a friction force, $-k\dot{\mathbf{x}}^{\text{PW}}$, and a equally strong but oppositely directed force as the waiters preferred force, $\mathbf{F}^{\text{PW}}$.

We now have three free model parameters in the APPM: k , M , and d . To study the stability of the APPM, we will take a similar approach as for the PPM, we consider the equations of motion of a free waiter within the distance d of its preferred position,

$$\ddot{\mathbf{x}} = \frac{1}{\tau} \left(\frac{v^{\text{P}}}{d} (\mathbf{x}^{\text{PW}} - \mathbf{x}) - \dot{\mathbf{x}} \right), \quad (4.10a)$$

$$M\ddot{\mathbf{x}}^{\text{PW}} = -m\ddot{\mathbf{x}} - k\dot{\mathbf{x}}^{\text{PW}}. \quad (4.10b)$$

These four ordinary differential equations are pairwise coupled; the two equations for the first coordinate of $\mathbf{x}$ and $\mathbf{x}^{\text{PW}}$ are coupled to each other, but this pair of equations is uncoupled from the pair of equations for the second coordinate.

The question now is if it is possible to choose the values of the parameters k and d so that the behavior of the system becomes analogous to the behavior of the PPM, that is, the waiter walks to the preferred position as quickly as possible and stops there, without oscillating, while at the same time the preferred position is dragged toward the waiter?

To this end we introduce the position of the waiter relative to the preferred position,

$$\mathbf{z} = \mathbf{x}^{\text{PW}} - \mathbf{x}, \quad (4.11)$$

Using the relative position of the waiter in the equations of motion, equations (4.10), gives

$$\ddot{\mathbf{x}}^{\text{PW}} + \frac{1}{\tau} \dot{\mathbf{x}}^{\text{PW}} = -\ddot{\mathbf{z}} - \frac{1}{\tau} \dot{\mathbf{z}} - \frac{v^{\text{P}}}{\tau d} \mathbf{z}, \quad (4.12a)$$

$$\ddot{\mathbf{x}}^{\text{PW}} + \frac{k}{M+m} \dot{\mathbf{x}}^{\text{PW}} = -\frac{m}{M+m} \ddot{\mathbf{z}}. \quad (4.12b)$$

If we set

$$k = \frac{M+m}{\tau} \quad (4.13)$$

we see that the motion of the waiter relative to the preferred position becomes decoupled from the motion of the preferred position,

$$\tilde{M} \ddot{\mathbf{z}} + \frac{1}{\tau} \dot{\mathbf{z}} + \frac{v^{\text{P}}}{\tau d} \mathbf{z} = \mathbf{0}, \quad (4.14a)$$

$$\ddot{\mathbf{x}}^{\text{PW}} + \frac{1}{\tau} \dot{\mathbf{x}}^{\text{PW}} = -\tilde{m} \ddot{\mathbf{z}}, \quad (4.14b)$$

where the dimensionless relative mass parameters

$$\tilde{m} = \frac{m}{M+m}, \quad (4.15)$$

and

$$\tilde{M} = \frac{M}{M+m}, \quad (4.16)$$

have been introduced. Thus we have recovered the behavior of the PPM, the equation of motion of the waiter is a damped harmonic oscillator with the preferred position as equilibrium position, but now the preferred position is moving.

We now follow the same procedure as with the PPM, we demand that the motion of the waiter, relative to the preferred position, should

be critically damped, so that the waiter moves as quickly as possible to the preferred position, but without oscillating. Thus, the choice

$$d = \frac{4\tau v^p}{\tilde{M}}, \quad (4.17)$$

gives a solution $\mathbf{z}(t)$ in which both coordinates decreases exponentially. The same is true for the acceleration, $\ddot{\mathbf{z}}$, which is the right hand side of equation (4.14b), so also the speed of the preferred position will decrease exponentially. These properties indicate that the model is stable; for any small perturbation of a waiter, such that it is still located within the distance d of its preferred waiting position, the waiter and its preferred position will return to rest at a new adapted waiting position, located some distance from the original waiting position. This distance depends on the value of M ; a higher value gives a smaller adjustment.

The above discussion shows that the model behaves properly for small perturbations of the waiter. But what about stronger perturbations? One could imagine that if the waiter is forced far away by a large crowd, the heavy preferred position could accumulate sufficient momentum to pass the waiter and drag it away. This behavior would render the model useless. Thus, we now consider the largest possible perturbation of a waiter and show that the model still behaves in a stable and suitable way.

From equations (4.9) we see that the size of preferred force, F^{pw} , which is the same as the size of the force applied to the preferred position, attains a maximum when the waiter is walking at its maximum speed in the opposite direction of its preferred velocity. We assume that the pedestrian is forced to such motion by external forces for a prolonged period of time. Without loss of generality we can study the one dimensional problem; we get the equation of motion for the preferred position

$$\tilde{M}\dot{x}^{pw} + \frac{1}{\tau}\dot{x}^{pw} = \frac{\tilde{m}}{\tau}(v^p + v^{\max}), \quad (4.18)$$

which is a first order ordinary differential equation for $\dot{x}^{pw}$, that, given the initial condition, $\dot{x}^{pw} = 0$, has the solution

$$\dot{x}^{pw}(t) = \tilde{m}(v^p + v^{\max})(1 - e^{-t/\tilde{M}\tau}). \quad (4.19)$$

The preferred position thus approaches its maximum velocity

$$\dot{x}_{\text{MAX}}^{\text{PW}} = \tilde{m}(v^{\text{P}} + v^{\text{MAX}}), \quad (4.20)$$

as the time goes to infinity.

Since both the speed of the waiter and the speed of the preferred position are bounded, and both decrease exponentially as soon as they are within a distance d of each other, the waiter will return to rest shortly after the perturbing force disappears.

4.6 The importance of modeling waiting behavior

The waiting models proposed in this chapter assume different behaviors of the waiting pedestrians. The PVM assumes that waiting pedestrians do not care exactly where they wait, which results in a drift away from passing traffic, the PPM assumes that waiting pedestrians always return to their preferred waiting position, and the APPM assumes an adaptive version of the behavior of the PPM. We will quantify the implications of these differences in more detail in chapter 7, since this analysis requires the development of suitable measures to characterize pedestrian traffic, which will be presented in chapter 6.

However, we will now show the importance of using a suitable model of waiting behavior in simulations where the object is to predict the delay or travel time of pedestrians. We will do this by comparing the predicted delay of passing pedestrians caused by a group of waiting pedestrians, when applying the different waiting models. The delay or travel time of walkers is one of the most important outputs of a simulation performed to evaluate the performance of the simulated infrastructure. Thus if the different waiting models leads to significantly different predictions of the delay, the importance of choosing an accurate waiting model is proven. The delay is simply defined as the difference between the experienced travel time of the walker and the travel time the walker would have experienced if it walked along the shortest path at its preferred speed.

The simulated scenario consists of a straight corridor, in the middle of which a group of pedestrians is waiting in front of an information sign at $\mathbf{x}^{\text{F}}$. The walkers are created at one end of the corridor ran-

domly spread over its width. The mean rate by which the walkers are created was chosen to be 2.6 s^{-1} , so that the walkers arrive in a relatively dense burst. Such sudden bursts are common in public transport interchange stations after the arrival of a public transport vehicle. Since the walkers are created at random points in the origin, some will be created closer to each other than they would prefer, so some initial interactions between the walkers will take place. The waiting area, ω , is placed 12 m from the origin so that the initial interactions between the walkers should not affect the interactions between the walkers and the waiters. The details of the geometry of the scenario can be seen in figure 4.5.

Figure 4.5: The geometry of the simulation scenario designed to investigate the predictions of the different waiting models.

The walkers with the the waiting area as destination are created a sufficient time before the other walkers to have time to reach ω and settle down before the passing walkers arrive. The preferred position in the PPM and APPM has to be assigned in some way. A suitable way to do this in the general case is an interesting topic for future research, as it may depend on lots of factors, such as the distribution of waiters already present and the distribution of passing traffic when the decision is made, and of course personal preferences. Here we assume a very simple but reasonable scheme to choose the preferred position. As they enter the waiting area, the PPM and APPM waiters choose the closest point that is 2 m from the information sign as their preferred position.

To study the effect a waiting group has on the delay experienced by a passing group of walkers, two experiments were performed with each waiting model, one with 10 passing walkers and one with 100 passing walkers. In both experiments there were 10 waiters. Also a reference experiment without any waiters was performed.

Due to the differences between the waiting models it is expected that the delay experienced by the passing walkers will differ slightly when different waiting models are used. The *pvm* waiters will move to the side when interacting with the first passing walkers and are thus expected to cause less delay for the remaining walkers. The *ppm* waiters, on the other hand, are expected to return to their preferred position and thus interfere with a larger fraction of the walkers. For the *appm*, $M = 4$, and $m = 1$, was chosen, so the result is expected to fall somewhere in between those of the *pvm* and *appm*.

The experiments were repeated 100 times for each model. In each repetition the total delay of each walker was calculated, starting when the walker passed 7 m from the origin to avoid inclusion of the delay caused by the initial interactions. The mean delay for each repetition, and then the mean over all the repetitions, together with its 95 % confidence interval, is presented in figure 4.6.

Figure 4.6: The mean delay per passing walker in the case with 10 and 100 passing walkers, white and gray bars respectively. In both cases there are 10 waiters, except for the ‘Empty’ case, in which there are no waiters. The data is based on 100 repetitions of the simulation in each case, and the error bars represent the 95 % confidence intervals. In the *appm* simulations $M = 4$.

As can be seen in figure 4.6, there is a significant contribution to the delay caused by the presence of the waiters. Further there are significant differences in the delay predicted by the *pvm* and the *ppm*. This difference is more evident if we only consider the additional delay caused by the waiters. We can estimate this additional delay by

subtracting the delay of the "Empty" scenarios from each of the others. The results are convincing; the PPM predicts a more than 30 % higher additional delay than the PVM. Thus we can conclude that the inclusion of waiting behavior in a model may have a significant impact on the predictions of the simulations, and that the choice of waiting model also is important for the predictions.

The general conclusion, that the inclusion of waiting walkers in pedestrian simulation models are important, confirming the conclusion of Davidich et al. (2013), is supported by nature of the used waiting models; the operative level of the behavior of the waiters are still controlled by the SFM which makes them rather helpful, moving out of the way of the passing pedestrians. The simulations are therefore likely to produce low estimates of the delay.

We have so far only discussed the predictions of the models on a highly aggregated level. However, since the models used here are microscopic we may also obtain results regarding the distribution of delays among the walkers. In figure 4.7, the frequency of total delays of walkers are plotted in the form of histograms with 0.5 s wide bins. The result is from the experiment with 100 walkers, thus, the frequency on vertical axis represents the mean number of walkers in an experiment that has a total delay in each interval.

Figure 4.7: The distribution of total delays per walker in the experiment with 100 walkers. The total delay of each walker from 100 repetitions of the simulation for each model were used to create these four histograms. Each bin in the histograms is 0.5 s wide.

From the delay distribution we can see that the PPM causes more large delays, around 4 s to 8 s, than the PVM; so much more that it compensates the additional small delays, around 0 s to 4 s, that the PVM

causes compared to the PPM. This may be due to a higher probability in the PPM for a walker to encounter several waiters.

The negative delay apparent in figure 4.7 is a general feature of the applied version of the SFM and will be discussed further in chapter 7.

The results presented here may be affected by the absence of a dynamic route choice model. If such model would be included it is expected that the walkers would aim for gaps in the group of waiters. This could result in lower delays in general. The results may also be affected by an effect related to the difference between the PVM and the other two models. Since there is no preferred position in the PVM, the waiters will be spread out more evenly than when the other two models are used. This may account for parts of the difference between the PVM and the other two models. The PPM and the APPM are, however, compared under identical circumstances.

Since we have concluded that the three model extensions predicts different levels of delay, the importance of choosing the best model is obvious. However, observing the delay of pedestrians is not sufficient to determine which model should be used, so we need other ways to determine which of the models that describes real pedestrian traffic most accurately. In chapter 7, we take a first step in this direction by investigating the differences between the models in terms of the movement of the waiters.

Chapter 5

The Pedestrian Traffic Simulation Platform

APPLYING the SFM to provide predictions of future traffic conditions at pedestrian facilities implies implementing the model as part of a computer program. This is necessary since the model consists of one differential equation *for each* walker present. Due to the interactions between the walkers, these differential equations are coupled to each other through the interaction force. Thus, applying the SFM consists of solving a system of coupled differential equations, with as many equations as the number of walkers present under the studied period of time. This cannot be done efficiently with pen and paper other than under very restrictive assumptions; in the general case it must be done by a computer.

The SFM is, as has been discussed in previous chapters, only a model of the operational level of pedestrian behavior; it does not describe the route choice or activity choice of pedestrians. More specifically, the SFM needs the preferred velocity of each walker at each point in space and time as input to be able to describe the interactions between the walkers. Thus, the SFM needs to be supplemented with other models of these higher level behaviors to be able to represent the traffic in nontrivial environments.

This chapter describes the implementation of a simulation platform based on the SFM, including models for the behaviors of the

higher levels of the model hierarchy. The simulation platform is simply called the Pedestrian Traffic Simulation Platform (PTSP).

5.1 Motivation

This section will motivate the development of the PTSP, and its accompanying technical documentation.

One of the main purposes of this thesis is to investigate the properties and extend the capabilities of the SFM. This should be done in a scientific way, which implies that the methods used have to be transparent and all experiments have to be reproducible. To be able to do anything in this direction, an implementation of the SFM must be available.

There are already commercial softwares for traffic simulation available, that use the SFM as a basis for the behavior of the walkers in the simulations. Such commercial simulation programs provide all the conveniences of modern software, such as a more or less user friendly Graphical User Interface (GUI), beautiful 3D animations of the resulting traffic, more or less efficient handling of output data, etc. Such features are invaluable for practitioners applying simulation in their daily work to improve the traffic conditions in existing and planned infrastructure. However, being commercial, such programs provide a limited insight into the details of the implementation, and are thus also hard to modify by the user.

The demand of transparency and reproducibility disqualifies the usage of software of which the implementation details are unavailable, since transparency is lost and the experiments are only reproducible until a new version of the software is released. Due to these problems with the available commercial simulation platforms, a pedestrian traffic simulation platform had to be implemented to enable the research presented in this thesis.

To provide transparency of the framework and to guarantee the reproducibility of the experiments the PTSP is thoroughly documented, and the documentation is published as a freely available report (F. Johansson, 2013). Without this documentation the platform would not fill any purpose; it would be even more oblique than the commercial platforms.

In addition to providing information to researchers interested in the details of the models used, the documentation and its publication was made to expose the implementation to review. The corresponding practice is completely obvious for model development; no one would publish results of a simulation without a thorough explanation of the underlying model. Unfortunately this is not as obvious for the implementation of the model. This is especially unfortunate in the case of simulation platforms such as the PTSP, since such frameworks contain many small models and assumptions that must be made to get the simulation running. Thus the documentation of the PTSP is a contribution in itself.

5.2 Model specification

As described in chapter 3, there are many versions of the SFM, and each version has a set of parameters. In this section the version of the SFM that is implemented in the PTSP is specified, while the default parameter values are given in appendix A.

In addition to the SFM, a route choice model is needed that describes the preferred walking direction of the walkers at each point in space and time. For each destination d , this vector field is given by

$$\mathbf{v}_i^p(\mathbf{x}) = -v_i^p \frac{\nabla \phi_d(\mathbf{x})}{|\nabla \phi_d(\mathbf{x})|}, \quad i \in \mathcal{I}_d, \quad (5.1)$$

where $\mathcal{I}_d$ is the subset of walkers with destination d and $\phi_d(\mathbf{x})$ is the shortest walkable distance to the destination d , obtained by solving

$$|\nabla \phi_d(\mathbf{x})| = C(\mathbf{x}), \quad (5.2)$$

where

$$C(\mathbf{x}) = \begin{cases} 1, & \mathbf{x} \in \Omega, \\ M, & \mathbf{x} \in \partial\Omega, \end{cases} \quad (5.3)$$

and

$$\phi_d(\mathbf{x}) = 0, \quad \mathbf{x} \in \Delta_d, \quad (5.4)$$

where Ω is the walkable area, $\partial\Omega$ its border, that is, all kinds of obstacles, including walls; $\Delta_d \subset \Omega$ is the destination area, and M is a large constant.

The preferred force of walker i is given by the standard form, equation (3.1),

$$\mathbf{F}_i^p = \frac{1}{\tau} (\mathbf{v}_i^p - \dot{\mathbf{x}}_i), \quad (5.5)$$

where the preferred speed, v_i^p , is given as a truncated Gaussian distribution over the population. The parameter τ is assumed to be constant over the population.

The interaction force is given by the gradient of the potential

$$V_{ij} = F_0 \sigma e^{-b(\mathbf{r}_{ij}, \dot{\mathbf{r}}_{ij})/\sigma}, \quad (5.6)$$

where the shape $b(\mathbf{r}_{ij}, \dot{\mathbf{r}}_{ij})$ is given by the elliptic relative velocity specification, equation (3.8), as

$$b(\mathbf{r}_{ij}, \dot{\mathbf{r}}_{ij}) = \frac{1}{2} \sqrt{(r_{ij} + |\mathbf{r}_{ij} + \dot{\mathbf{r}}_{ij} T_s|)^2 - (\dot{r}_{ij} T_s)^2}, \quad (5.7)$$

where the anticipation time parameter T_s is assumed constant over the population.

The anisotropic weight of the interaction force is given by equation (3.14) with $\lambda = 0$, that is the maximal anisotropy of that functional form of the weights,

$$w(\mathbf{e}_i, \varphi_{ij}) = \frac{1 + \cos \varphi_{ij}}{2}. \quad (5.8)$$

The physical force between walkers is given by

$$\mathbf{F}_{ij}^{\text{PHYS}} = \frac{\mathbf{r}_{ij}}{r_{ij}} F_0^{\text{PHYS}} e^{(2R - r_{ij})/\sigma^{\text{PHYS}}}, \quad (5.9)$$

where the walker radius R , the strength F_0^{PHYS} , and the range σ^{PHYS} are assumed constant over the population.

The obstacle force is given by

$$\mathbf{F}_{in}^{\text{OBST}} = F_0^{\text{OBST}} \frac{\mathbf{r}_{in}}{r_{in}} e^{-r_{in}/\sigma^{\text{OBST}}}, \quad (5.10)$$

where both F_0^{OBST} and σ^{OBST} are assumed constant over the set of obstacles.

Finally the random force, $\mathbf{F}^{\text{RAND}}$, at a given point in time is a random variable with a Gaussian distribution.

The equations of motion are

$$\mathbf{a}_i = \mathbf{F}_i^p + \sum_j \left(w(\varphi_{ij}) \mathbf{F}_{ij} + \mathbf{F}_{ij}^{\text{PHYS}} \right) + \sum_n \mathbf{F}_{in}^{\text{OBST}} + \mathbf{F}^{\text{RAND}}, \quad (5.11a)$$

$$\dot{\mathbf{v}}_i = \mathbf{a}_i, \quad (5.11b)$$

$$\dot{\mathbf{x}}_i = \frac{\mathbf{v}_i}{v_i} \min \left\{ v_i, v_i^{\text{MAX}} \right\}, \quad (5.11c)$$

where the maximum speed of walker i is assumed to be $v_i^{\text{MAX}} = \gamma v_i^p$, where $\gamma > 1$ is assumed to be constant over the population.

5.3 Implementation structure

The PTSP is in no way intended to compete with the commercially available simulation tools, it is meant to function as a research tool, rather than a tool for performing large scale systematic simulation studies. Thus a central design decision underlying the PTSP is that it should be easily modified and extended at the source code level. The flexibility, and even user friendliness at the user level, are secondary objectives. With this and the general form of the problem in mind, an object oriented approach was chosen. Object orientation naturally provides a modular structure which gives the sought flexibility.

When performing simulations and developing simulation models the availability of a direct graphical representation of the simulated traffic is of great value, both for understanding the simulated phenomena and for verifying that the implementation works correctly. To meet this need the Qt framework was chosen as basis for the development (Qt-Project, 2013). This choice also enables quick development of a basic cross platform compatible GUI.

One aspect of the fact that the PTSP is mainly intended for research is that there is no clearly defined final form of the software. Rather, the development process, and the program structure itself, have to be flexible enough to allow the development to follow the requirements of the research process. Thus, it makes no sense to develop an optimal program structure meeting the current requirements, since these are likely to change; flexibility is the main design principle.

The most important class in the PTSP is of course the `Walker` class, objects of which are representing the pedestrians walking through

the studied infrastructure.

The strategical level of the model is regarded as input data. The origins and destinations of walkers are represented by objects of the *Origin* and *Destination* classes. The origins create walkers randomly at a given rate within a given area, with a given distribution of activity lists. The activity list of a walker is basically an ordered list of destinations. As the walker reaches the final destination in its activity list it is destroyed.

The route choice to each destination in the activity list consists of a shortest path algorithm implemented using a discretized representation of the simulated area. This representation is a grid that consists of square cells that can either be walkable or not, that is, be part of the walkable area or part of an obstacle. For each destination, the shortest path algorithm produces, in each walkable cell in the grid, an approximation of the direction of the tangent of the shortest walkable path to the destination. In addition to this representation of the geometry of the simulated facility there is another vector field on an equivalent grid describing the repulsive obstacle forces of all obstacles. This field is, as the navigation field, calculated only once at the start of the first of a sequence of simulations.

The obstacle force field is a part of the operational level of the model. The remainder of that level is implemented in the *Walker* class. A walker object has a set of variables describing the state of the walker, such as its position and velocity, and also its current activity, waiting or walking, and information regarding its destinations. The walker class also contains the implementation of the *SFM* specified in section 5.2.

In addition to these classes that represents elements of the real world there are several book keeping classes that communicate information, handle data collection, and manage the GUI and the graphical representation of the simulated scenario. The central class is the *Simulator* class, which is responsible for the main simulation loop, depicted in figure 5.1, and it also keeps record of all object of the simulation. The simulator is owned by an instance of the *SimWindow* class, which is a subclass of the main GUI class of the Qt framework. This class handles the main event loop of the application and the GUI.

5.4 Implementation details

In section 5.2 the mathematical model was summarized, and in section 5.3 the general structure of the PTSP was outlined from a software point of view. In this section the implementation details of the most central parts of the model are described; only parts that directly affect the results of the simulations are included, while the parts handling the GUI, output and input data, and animations, are omitted. A complete description of all details of the implementation is presented by F. Johansson (2013).

The strategical level of the model consists of input data in the form of input flows and activity lists. The objects that handle this are objects of the classes `Origin`, `Destination`, and `WalkPath`.

Objects of the `Origin` class represent places where pedestrians enter the simulated area. Depending on the nature of the simulated area, and especially its borders, these entrances may be a number of different infrastructure elements such as doors, pedestrian crossings, stairways, elevators, public transport vehicle doors, or even a wide segment of open ground. Each origin is associated with an area, in which it creates walkers, randomly distributed over the area according to a user defined probability distribution. The walkers are created with random time gaps, also these specified by a user defined probability distribution. When a walker is created at an origin, the time gap to the next walker that should be created at that origin is generated. At each time step of the simulation, in the *create walker* phase of figure 5.1, each origin tests if more time than the generated time gap has passed since the last walker was created at that origin.

The activity list of a walker is assigned to it by the origin it was created by. The activity list is represented by objects of the class `WalkPath`, which basically is an ordered list of destinations. Each origin has a set of `WalkPaths` and associated probabilities, corresponding to the fractions of walkers created at that origin that should have the corresponding activity list. When a walker is created at an origin a random draw is made to determine which of the activity lists it should follow.

Objects of the `Destination` class represent both final and intermediate destinations. Final destinations are such destinations where walkers exit the simulated area. The last destination in the `WalkPath`

of a walker is always interpreted as a final destination, and the walker is destroyed when this destination is reached. The other destinations in the `WalkPath` of a walker are interpreted as intermediate destinations, and when a walker reaches one of those it is assigned a waiting time from a user specified distribution corresponding to that destination, and its state variable `Activity` is updated to `Waiting`. The walker waits at the intermediate destination until the waiting period has ended, and the `Activity` is changed back to `Walking`, before continuing to the next destination in the list.

The geometry of the facility is represented through the configuration of objects of the `Obstacle` class. Any point which is not walkable is part of an obstacle or enclosed by obstacles. An object of the `Obstacle` class consist of a single line segment; more complex obstacles are represented by several `Obstacle` objects. Obstacles influence the movements of walkers in two ways, through the route choice to the next destination, and through the obstacle force, equation (5.10).

The route choice of the walker on its way to the next destination in its list is determined by a shortest path algorithm. This algorithm takes a discretized representation of the infrastructure and the location of a destination area as input and produces at each walkable cell of this discretized representation an approximation of the normalized tangent of the shortest walkable path from that point to the destination. This is achieved by solving equation (5.2) with boundary conditions described by equation (5.3).

However, solving the above problem would result in preferred paths passing very close to corners of obstacles; the obstacle force would then force the walker away from the corner, resulting in strange behavior. An inconsistent desire of the walker would appear; it would aim for a point close to a corner, where it would not wish to be. Therefore, all obstacles are extended by 0.4 m before the route choice model is executed, making the walkers aim for points at a comfortable distance from obstacle corners.

Equation (5.2) with boundary conditions described by equation (5.3), with the modifications of the previous paragraph, is solved using the Fast Marching Method (FMM) by Sethian (1996). The FMM solves the problem by constructing the solution $\phi_d(\mathbf{x})$ outward from the destination area where it is known.

This is achieved using the approximation

$$\frac{\partial \phi}{\partial x} \approx \max \{ D_k^{-x} \phi, -D_k^{+x} \phi, 0 \}, \quad (5.12)$$

where D_k^{-x} and D_k^{+x} are the finite difference operators,

$$D_k^{\pm x} \phi = \pm \frac{\phi_k - \phi_{k \pm 1}}{h}, \quad (5.13)$$

and the x -coordinate is discretized according to $x = kh$; ϕ_k and $\phi_{k \pm 1}$ are the values of $\phi(\mathbf{x})$ at $\mathbf{x} = (kh, lh)$ and $\mathbf{x} = ((k \pm 1)h, lh)$, respectively, where h is the size of a cell. The destination index d has been dropped for clarity. This approximation has the property that it only depends on the values of the neighbors of $\phi_{k,l}$ that are smaller than $\phi_{k,l}$. When this approximation of the gradient is used in equation (5.2), we obtain

$$\begin{aligned} & \left(\max \{ D_k^{-x} \phi, -D_k^{+x} \phi, 0 \} \right)^2 \\ & + \left(\max \{ D_l^{-y} \phi, -D_l^{+y} \phi, 0 \} \right)^2 = F^2. \end{aligned} \quad (5.14)$$

When the equation is solved for the value of ϕ at position (k, l) , this value can only depend on the neighboring values that are smaller than the calculated value, due to the corresponding property of the approximation of the gradient. Note that this equation has two roots, but it is only the larger one that is consistent with the definition of the approximation of the gradient. By solving equation (5.14) we can calculate an approximation of the solution at the points neighboring the area where the solution already is known by using only the known values, since none of the later calculated values will be smaller than these. These newly calculated values will form a narrow band around the known area. From the property that new values only depend on smaller values, it is clear that the smallest calculated value in the narrow band can not be affected by continuing the procedure by extending the band and recalculate all values, since all these new values will be greater. Thus we can fix the smallest value in the narrow band and update its greater, non fixed, neighbors. Then the smallest value in the partly new narrow band can be fixed, and so on. In this way the solution is constructed outwards from the destination in a computationally efficient manner. The algorithm can be summarized as

follows.

Initiation:

- 1 Set the distance at points in the destination area to zero and tag them as *Frozen*.
- 2 Tag all non-*Frozen* points in the walkable area *Far*, and all points in obstacles as *Obstacles*.
- 3 Tag points neighboring *Frozen* points as *Close* and set the distance to each *Close* point to the largest solution of (5.14).
- 4 Create a list with the *Close* points always kept sorted according to their distance with the smallest first.

Loop:

- 1 Remove the first entry (smallest) in the list of *Close* points and tag it as *Frozen*.
- 2 Set the distance in its non-*Frozen*, non-*Obstacle* neighbors to the largest solution of (5.14) and tag them as *Close* and add them to the list if they were *Far*.
- 3 Goto 1 if the list of *Close* points is non-empty.

The *SFM* part of the *PTSP* is straight forward to implement through the simple Euler method. This is done in the *update forces* and *update state* phases of figure 5.1.

To calculate the forces the Simulator loops over all walker objects and for each of them calculates each of the forces from its state. The calculation of the interaction force is performed by looping over all other walkers, resulting in an expensive double loop, which makes the running time of the algorithm $O(N^2)$, where N is the number of walkers present in the simulation simultaneously.

In the *update state* phase the position is updated by the current velocity,

$$\mathbf{x}_i(t + \Delta t) = \mathbf{x}_i(t) + \dot{\mathbf{x}}_i \Delta t, \quad (5.15)$$

$\mathbf{v}_i$ is updated with the acceleration calculated from the forces,

$$\mathbf{v}_i(t + \Delta t) = \mathbf{v}_i(t) + \mathbf{a}_i(t) \Delta t, \quad (5.16)$$

and bounded by the maximum velocity,

$$\dot{\mathbf{x}}_i(t + \Delta t) = \frac{\mathbf{v}_i}{v_i} \min\{v_i, v_i^{\text{MAX}}\}. \quad (5.17)$$

It is also in this phase that the preferred velocity is calculated. If the Activity of the walker is *Walking*, the preferred velocity is calculated by reading its direction from the pre-calculated navigation field and scaling it with the preferred speed. If on the other hand the Activity is *Waiting*, the preferred velocity is calculated according to the chosen waiting model.

Further details on the implementation are given by F. Johansson (2013).

Figure 5.1: The main simulation loop of the PTSP

Chapter 6

Measures of pedestrian traffic conditions

A fundamental problem for microscopic traffic simulation models is the question of how to draw conclusions from the huge amount of detailed output data that is produced.

Almost all microscopic models are stochastic to take into account the limitations of the model and the intrinsic randomness of pedestrian behavior. This means that the output of simulations based on such models should be treated in a statistical manner. The simulation model can be seen as a complicated stochastic variable, with the sample space consisting of all possible trajectories of all the simulated walkers. But we are seldom interested in the trajectories of individual walkers, and in addition it is not likely that the sample space of the model represents the sample space of the real situation at that level of detail, due to limitations in data and the model itself.

The kind of output data that is interesting from an application point of view is the average, or expected traffic situation at a higher level of aggregation. The higher the level of aggregation, the fewer simulation repetitions are needed to estimate expected traffic state with a given level of confidence. We will never have enough computational power to estimate the probability distribution of the microscopic state of the system, while a highly aggregated description may be estimated by just a few runs. Of course, as we increase the level

of aggregation we also increase the risk of losing *important* details in the aggregation process.

An interesting problem is how to determine the level of aggregation such that the output data captures the interesting details and not too much more. This problem is the subject of the present chapter. First, in section 6.1. the traditional way of quantifying pedestrian traffic is presented, followed, in section 6.2, by the proposal of new *local* measures.

6.1 Traditional measures

The measures used to describe the traffic situation is naturally dependent on the level of detail with which the traffic can be observed. One of the most basic traffic measures, which is also easy to obtain, is the flow through a cross section with dimension s^{-1} , that is, the number of pedestrians passing a cross section per unit time.

The flow is of course dependent on the width of the cross section, and in order to compare the conditions at infrastructure elements of different widths the specific flow is usually used instead, which is the flow per unit width, with dimension $s^{-1} m^{-1}$.

Another basic measure is the average density in an area, that is, the number of pedestrians within a pre-specified area at a specific moment in time, with dimension m^{-2} . Sometimes the inverse density, occasionally called pedestrian area module, is used.

Using these two measures, Fruin (1971) developed a Level of Service (LOS) classification scheme, assigning a letter A–F to the traffic situation in walkways and stairs depending on the specific flow or density. LOS A corresponds to free flow conditions, where pedestrians can pass each other conveniently, and LOS F corresponds to the critical density with only sporadic flow and involuntary physical contact between pedestrians. Fruin (1971) developed threshold values for each level, for three different types of pedestrian infrastructure elements, walkways, stairs, and queuing or waiting areas. The thresholds for stairs and walkways are based on both density and flow, while the queuing area's LOS naturally only depends on the density.

Measures on this very aggregated level are useful since they are relatively easily measured in real traffic situations, and can efficiently be used as guidelines for designers and operators of pedestrian facil-

ities. The LOS measures by Fruin (1971) are with little modification included in both Kittelson & Associates, inc. et al. (2003) and TRB (2010).

This type of measures are, however, limited in that there must be a naturally enclosed area or cross section to calculate the density or flow over. If no such natural structure exists the measures may of course still be formally calculated over any chosen area or cross section, but then the resulting classification may depend strongly on the exact choice of the area. The measures are also limited in that they do not take the structure of the flow into account.

In vehicular traffic the mean speed of the vehicles on a link serves as a good measure of the LOS on that link. This is, however, harder to translate to the pedestrian setting for two reasons. First, it is much harder to measure the average speed in chaotic multi-directional pedestrian traffic, than in ordered unidirectional vehicle traffic. Second, the velocity of a pedestrian need not be in the direction she or he prefers to move, evasive maneuvers may cause the pedestrian to move at an angle to the preferred direction, but still with its preferred speed, which is obviously not as good as walking in the preferred direction with the preferred speed. The average speed is thus only a useful description of the traffic situation when the flow is structured, so that a uniform walking direction, that coincides with the preferred direction, can be defined.

Another approach, applicable when detailed data is available, is to aggregate over a population instead of over an area. A typical example of this approach is the average travel time for pedestrians between a specific OD pair, belonging to any type of category. This type of measure is useful for evaluation of the global level of service of the facility, but does not assign the properties to a physical location. Other possibilities in addition to travel time is average speed or how much the pedestrians accelerate during their trip through the facility.

The amount of accelerations performed may be seen as a measure of the discomfort of the traffic situation since it represents how many and how large evasive maneuvers that are needed. As a measure of the amount of acceleration performed by the pedestrians, Helbing and Molnár (1997) propose a measure based on how much the velocity of the pedestrians deviate from their mean velocity, according

to

$$D_H = \frac{1}{N} \sum_{i=1}^N \frac{\langle (\dot{\mathbf{x}}_i - \langle \dot{\mathbf{x}}_i \rangle_t)^2 \rangle_t}{\langle \dot{\mathbf{x}}_i^2 \rangle_t}, \quad (6.1)$$

where the sum is taken over all, or a subset of, the pedestrians. Here, $\langle \cdot \rangle_t$ denotes the time average during some time interval. The authors also propose a measure of the efficiency of the flow,

$$E = \frac{1}{N} \sum_i \frac{\langle \dot{\mathbf{x}}_i \cdot \mathbf{v}_i^p \rangle_t}{(v_i^p)^2}, \quad (6.2)$$

assuming that the preferred velocities of the pedestrians are known, as is the case if the considered data is the output of a simulation. A related measure is of course the average delay,

$$T^{\text{DELAY}} = \frac{1}{N} \sum_i (T_i - T_i^{\text{FREE}}), \quad (6.3)$$

where T_i is the travel time of pedestrian i and T_i^{FREE} is what the travel time of pedestrian i would have been if it was walking at the preferred speed along the shortest path. An example of the usage of this measure is given in figure 4.6.

Measures of this type describe microscopic properties of the traffic situation, but aggregated up to a global level, which makes them interpretable in terms of averages, or expected values. A more disaggregated way of describing the same information is to consider the distribution of a measure over the population, instead of just the mean. Such an example is also given in figure 4.7.

6.2 Local measures

The problem with the traditional measures described in the previous section is that they either are averages over a manually defined area, and may depend strongly on the exact choice of that area; or are averages over the population, or part of the population, and measures the traffic conditions everywhere the included pedestrians have walked, when they walked there.

When applying microscopic simulation to a design or evaluation problem, we would like to aggregate the output data into measures

that describe the traffic situation with a level of detail such that the average properties of the traffic situation become clear and not occluded by irrelevant details, while still ensuring that no important feature of the traffic is averaged out. Furthermore, it would be preferable if the measures were continuous fields defined on the walkable area to simplify analysis of, and comparison between, cases.

One example of such a measure is the smoothed, or local, walker density used by Helbing et al. (2001) to describe the extreme densities during a crowding disaster. The local density is defined as

$$\rho_R(\mathbf{x}, t) = \sum_i \frac{1}{2\pi R^2} e^{-(\mathbf{x} - \mathbf{x}_i(t))^2 / 2R^2}, \quad (6.4)$$

where R is the spatial scale of the local density.

An equivalent way of viewing the local density is by regarding the distribution of walkers at time t , $g(\mathbf{x}, t)$, as a sum of Dirac delta distributions,

$$g(\mathbf{x}, t) = \sum_i \delta(\mathbf{x} - \mathbf{x}_i(t)), \quad (6.5)$$

then the density in a domain Ω , with area A_Ω , is

$$\rho_\Omega(t) = \frac{1}{A_\Omega} \sum_i \int_\Omega \delta(\mathbf{x} - \mathbf{x}_i(t)) d^2\mathbf{x}. \quad (6.6)$$

The local density can then be viewed as a filtered version of the distribution, which is obtained by convolving the distribution with a filtering function w ,

$$\rho_R(\mathbf{x}, t) = \int_{\mathbb{R}^2} w(\mathbf{x} - \mathbf{x}') g(\mathbf{x}' - \mathbf{x}_i(t)) d^2\mathbf{x}', \quad (6.7)$$

where w is a normalized filter, that is

$$\int_{\mathbb{R}^2} w(\mathbf{x}) d^2\mathbf{x} = 1. \quad (6.8)$$

Choosing

$$w(\mathbf{x}) = \frac{1}{2\pi R^2} e^{-\mathbf{x}^2 / 2R^2} \quad (6.9)$$

gives the definition in equation (6.4). Note that even though equation (6.4) and equation (6.7) are equivalent, either one may be more convenient when calculating the local density from data, depending on the encoding of the data.

The specification of the local density by the choice of filter, equation (6.9), is arbitrary, both in the shape of the filter and in the choice of scale parameter R . However, if the *sFM* is a good model for describing pedestrian dynamics, or at least when the *sFM* is used, we propose that the choice of the filtering function, equation (6.9), is the natural one, and furthermore, that there is a natural choice of the scale parameter of the filter, namely the range scale of the interaction force of the *sFM*.

The purpose of defining local measures is to aggregate features of the flow that in some sense belong together, but still resolve features that are separate from each other. Since the interaction force of the *sFM* is exponentially decreasing with the distance, with a range scale parameter σ , walkers that are much further apart than σ will not interact. Such a gap in the distribution of walkers should be resolved by a good local density measure, since it provides information about the structure of the traffic. On the other hand, walkers that are closer together, within a distance in the order of σ of each other, are interacting, and should be included in a common peak in the local density field. We propose that the choice of filter according to equation (6.9), with the scale parameter chosen as $R = \sigma$ is the natural choice for defining the local density. As will be demonstrated here, the filtering approach can also be used to define other local measures describing different aspects of the traffic situation at a suitable level of detail.

An important aspect when designing and evaluating pedestrian infrastructure is the discomfort perceived by the users due to congestion. The density captures some aspects of this discomfort, but not all; depending on the flow structure, different levels of discomfort may be perceived at a given density. An example is that a density that feels comfortable when the flow is unidirectional may feel highly uncomfortable when the flow is multidirectional. To capture this effect, a local measure that takes into account both the position and the velocity of the walkers is needed. Given a walker i and the relative position and velocity of a nearby walker j , we estimate the discomfort walker j causes walker i . We propose that the *sFM* is a suitable model to be used as a basis of a measure of the discomfort.

The very foundation of the *sFM* is the assumption that the aversion of pedestrians against walking to close to each other can be modeled

by the interaction force. Thus, assuming that the sFM is a sufficiently accurate model of pedestrian dynamics, the size of the interaction force between walkers should be a good proxy for the perceived discomfort of two pedestrians in the corresponding situation. Therefore, let f_{ij} be the size of the anisotropic interaction force between walkers of the sFM, $f_{ij} = |w(\varphi_{ij})\mathbf{F}_{ij}|$, so that the local discomfort density at time t becomes the filtered distribution,

$$\Delta(\mathbf{x}, t) = \sum_i \int_{\mathbb{R}^2} \sum_j f_{ij} \delta(\mathbf{x}' - \mathbf{x}_i(t)) w(\mathbf{x} - \mathbf{x}') d^2 \mathbf{x}'. \quad (6.10)$$

The integral is trivially evaluated, reducing the expression to

$$\Delta(\mathbf{x}, t) = \frac{1}{2\pi\sigma^2} \sum_i \sum_j f_{ij} e^{-(\mathbf{x} - \mathbf{x}_i(t))^2 / 2\sigma^2}. \quad (6.11)$$

The local measure Δ is the local instantaneous discomfort density, but discomfort is in general, and especially in this definition, something that is perceived continuously, and additively over time; thus Δ is better termed the local discomfort rate density. It is the rate at which discomfort is generated by the traffic per unit area, that is, if we integrate Δ over the whole plane and over all times, the result is the total discomfort resulting from the given traffic in the given facility.

This definition of the discomfort relies on a relatively literal interpretation of the sFM. Another measure of the discomfort, inspired by the discomfort measure by Helbing and Molnár (1997), equation (6.1), is the amount of evasive maneuvers, measured in terms of the magnitudes of the accelerations applied by the walkers. Thus, analogous to the local discomfort density, the local acceleration density becomes

$$A(\mathbf{x}, t) = \sum_i \int_{\mathbb{R}^2} a_i \delta(\mathbf{x}' - \mathbf{x}_i(t)) w(\mathbf{x} - \mathbf{x}') d^2 \mathbf{x}', \quad (6.12)$$

where $\mathbf{a}_i$ is according to equation (3.16).

However, it can be argued that small accelerations are not evasive maneuvers and should not contribute to the discomfort, so an alternative definition is

$$\tilde{A}(\mathbf{x}, t) = \sum_i \int_{\mathbb{R}^2} \theta(a_i - a_0) a_i \delta(\mathbf{x}' - \mathbf{x}_i(t)) w(\mathbf{x} - \mathbf{x}') d^2 \mathbf{x}', \quad (6.13)$$

where $\theta(a_i - a_0)$ is the Heaviside step function, and a_0 a threshold acceleration specifying how large an acceleration needs to be to contribute to the discomfort. The alternative form, $\tilde{A}$, will not be considered further here.

One of the most important measures of the efficiency of a traffic situation is the delay experienced by the traffic participants. As mentioned in the previous section it can be measured by the total delay, equation (6.3), but this does not reveal where the delay is caused. To define a localized measure of the delay, or rather the delay rate, we consider the difference in the rate at which the walker approaches its destination and the rate it would have approached its destination if it had walked at its preferred speed along the shortest path to its destination. Let $\phi(\mathbf{x}_i(t))$ be the distance to the destination for pedestrian i at time t . Since the walker would have approached its destination with its preferred speed, the rate at which the walker is delayed is

$$D_i = \frac{v_i^p - \dot{\phi}}{v_i^p}, \quad (6.14)$$

where the time derivative of the remaining distance, $\dot{\phi}$, is given by the component of the velocity of the walker that is in the direction of the preferred velocity,

$$\dot{\phi} = \frac{\mathbf{v}_i^p \cdot \dot{\mathbf{x}}_i}{v_i^p}. \quad (6.15)$$

Thus, the delay rate of walker i becomes

$$D_i = 1 - \frac{\mathbf{v}_i^p \cdot \dot{\mathbf{x}}_i}{(v_i^p)^2}. \quad (6.16)$$

Note that this is closely related to the efficiency measure of Helbing and Molnár (1997), equation (6.2).

Analogously to the other measures the delay rate density becomes

$$\Gamma(\mathbf{x}, t) = \sum_i \int_{\mathbb{R}^2} D_i \delta(\mathbf{x}' - \mathbf{x}_i(t)) w(\mathbf{x} - \mathbf{x}') d^2 \mathbf{x}'. \quad (6.17)$$

This is the delay produced per unit area and unit time, and if integrated over the whole area and all times, the total delay.

A disadvantage of the delay rate density is that it requires the preferred velocity of all walkers to be known. This is not a problem

for simulated traffic, but the preferred velocity may be hard to deduce from observations of real traffic. Usage of the delay rate density is thus restricted to simulation output.

Chapter 7

Simulation of pedestrian traffic scenarios

THE local performance measures proposed in chapter 6 are all reasonable measures of the discomfort caused by congestion in pedestrian traffic. The local density and the delay capture two aspects of the congestion induced discomfort, our aversion of walking too close to each other and our distaste of not being able to proceed as quickly as preferred. However, the density measure does not take into account that we care less about the situation behind us, nor the fact that we perceive more discomfort when people are rushing against us than if they walk in the same direction. And the delay measure does not include the fact that even if we can walk at our preferred velocity, crowded areas may feel uncomfortable. The discomfort measure captures this by using the SFM to quantify the influence of walkers on each other, and the acceleration measure captures it by using the amount of evasive maneuvers performed. The measures thus seem to be complimentary, capturing different aspects of the perceived traffic situation, but is this difference significant enough to motivate use of the full set of measures?

In the first section of this chapter this question will be examined by applying the measures to simulation results of the PTSP of some simple pedestrian traffic scenarios, and the difference between the measures will be examined. During this analysis we will also inves-

tigate if the proposed local measures can reveal new insights into the properties of the SFM.

In section 7.2, the measures will be applied to the simulation results of the experiments presented in section 4.6 to further investigate the differences between the three waiting models. Finally in section 7.3, a simulation of a railway platform will be presented and analyzed using the local measures, as an illustration of a realistic scenario.

7.1 Comparison of measures

To investigate to what extent the four local measures proposed in the previous chapter provide different information about the traffic situation, we apply the measures to a few basic pedestrian traffic scenarios. In addition to provide information on the degree of correlation between the measures, these experiments will indicate at what level of detail it is possible to describe the traffic situation based on the information provided by the measures.

7.1.1 Opposing flows

First, the results of two slightly different scenarios of opposing flows in a corridor are presented. The geometries of the scenarios are depicted in figure 7.1.

Figure 7.1: Schematic maps of the scenarios ‘Opposing unstructured flow’ (top) and ‘Opposing structured flow’ (bottom). Walkers created at O_A have D_A as destination and similarly for the pair O_B and D_B .

Both scenarios consist of a straight corridor, 50 m long, 8 m wide, with walkers created at both ends. In the first scenario, denoted *Opposing unstructured flow*, the walkers are created uniformly over the width of the corridor, at origins O_A and O_B , and have as destination the opposing end of the corridor, destinations D_A and D_B , respectively. In the second scenario, denoted *Opposing structured flow*, the walkers are not created uniformly over the width of the corridor, but only on one half of the width of the corridor, and have as destination the same half at the other end, as depicted in the figure. The specific rate at which walkers are created is equal in both scenarios, $0.43 \text{ s}^{-1} \text{ m}^{-1}$.

The results of five repetitions of the simulation are discussed in the following. The means of the time averaged local measures are presented in figures 7.2 to 7.5.

In figure 7.2, the mean local densities of both scenarios are depicted. We see that there is a noticeable difference between the two scenarios, the unstructured flow scenario in the top diagram reveals less structure, while the structured flow scenario has a lower density along the middle of the corridor. The local density resolves the important density variations and reveals the structure of the flow, even at as few as five repetitions of the simulation.

Figure 7.2: The replication and time averaged local density in the opposing unstructured flow scenario (top) and the structured scenario (bottom)

In figure 7.3, the mean discomfort densities of the two scenarios are depicted. In terms of the discomfort distributions, the differences between the two scenarios are clearly more pronounced than the dif-

ferences in density. In the structured flow scenario almost all discomfort is perceived in the boundary layer between the two flows, while the distribution in the unstructured case is random.

Figure 7.3: The replication and time averaged local discomfort density in the opposing unstructured flow scenario (top) and the structured scenario (bottom)

The mean of the acceleration density in figure 7.4, exhibits a similar pattern as the discomfort density. In the structured flow case, the majority of the evasive maneuvers are clearly preformed in the boundary layer while being much more random in the unstructured case.

Figure 7.4: The replication and time averaged local acceleration density in the opposing unstructured flow scenario (top) and the structured scenario (bottom)

The mean of the delay density, in figure 7.5, reveals that the delays

in the unstructured flow scenario is dominated by local peaks, indicating that much of the delay produced in this scenario is produced in relatively few high delay events. The delay density in the structured flow scenario is, somewhat surprisingly, at approximately the same level as in the unstructured scenario, and slightly more concentrated to the boundary layer between the two flows. However, a significant amount of the delay is produced within the unidirectional regions, possibly caused by a few stray walkers from the opposing side entering in to the area of homogeneous walking direction.

Figure 7.5: The replication and time averaged local delay density in the opposing unstructured flow scenario (top) and the structured scenario (bottom)

A comparison of the figures 7.2 to 7.5 suggests that the measures may be correlated; especially the discomfort density and the acceleration density seem to contain similar information. If this is the case it may be sufficient to only consider a subset of the measures. We therefore investigate the interdependence of the density and the other measures by plotting the value of each measure at a given time and place, against the value of the density at the same time and place. Since the two scenarios, the structured opposing flow and the unstructured opposing flow, contain fundamentally different traffic processes, we expect that the relationships between the measures will differ between the two scenarios.

In the top row of figure 7.6, the local discomfort density is plotted against the local density. We see that the slope of the cloud of points, for low densities, is lower in the structured flow scenario. It is rather obvious that the discomfort at a given density should be lower in the

structured flow scenario, since the flow to a large extent is locally unidirectional. However, it may be more surprising that the discomfort increases quicker with increasing density in the unstructured case, at least for densities below approximately 1 m^{-1} . At higher densities the discomfort seems to depend on the density in a similar way in the two scenarios. For high densities the discomforts seem to be almost equal, indicating that these events are caused by encounters of walkers moving in opposite directions, and are probably head on 'collisions'. A clear difference between the two scenarios is the presence of high discomfort, low density events. These are more frequent in the unstructured scenario, which is expected since these events can in principle only be caused by meeting walkers.

The dependence of the local acceleration on the local density is similar to that of the discomfort, but with a higher spread in general, see the bottom row of figure 7.6. Another difference between the acceleration density and the discomfort density is the presence of low acceleration densities for a long range of local densities, up to around 1.5 m^{-1} . In contrast, the lowest possible discomfort density increases with the density already from 0.5 m^{-1} . As a result there is a large spread in acceleration density for high density flows, implying that there may be very dense flows with low acceleration densities, while the discomfort density always is high for high densities.

Finally, the delay rate density is compared between the two scenarios. As can be seen in figure 7.7, the dependence of the delay rate density on the density is similar in the two scenarios, with exception of the frequency of outliers above the dense cloud. The frequency of high delay events is clearly higher in the unstructured scenario than in the structured scenario.

As can be seen in the results of both the structured and the unstructured scenario, there are some events with very low local density but still high delay rate densities. This means that there are situations when a walker is almost alone, locally, yet it is not moving at its preferred velocity. We must conclude that these events consist of the later stages of strong interactions between walkers; the most extreme low density, high delay events are walkers that have interacted, moved apart, but not yet adopted to the preferred velocity. Of course, these extreme events only contribute marginally to the total delay.

Figure 7.6: Top: Comparison of the relation between the local discomfort density and the local density in the unstructured flow scenario (left) and the structured flow scenario (right). Bottom: Comparison of the relation between the acceleration density and the pedestrian density in the unstructured flow scenario (left) and the structured flow scenario (right).

Figure 7.7: Comparison of the relation between the delay rate density and the pedestrian density in the unstructured flow scenario (left) and the structured flow scenario (right).

The above comparisons indicate that the local measures are useful to identify important details of the pedestrian traffic, and also that the measures contain different information about the system.

7.1.2 Crossing flows

Bidirectional flow is a common but special case of pedestrian traffic. Another simple and common pedestrian traffic scenario is depicted in figure 7.8. The scenario consists of two equally wide corridors, each with unidirectional flow, intersecting each other at a right angle. Two versions of this scenario is presented here, differing in the flow volume. In the first scenario the flow is twice that of the opposing flow scenario in the previous section, and in the second the flow is a quarter of the opposing flow scenario, that is $0.86 \text{ s}^{-1} \text{ m}^{-1}$ and $0.11 \text{ s}^{-1} \text{ m}^{-1}$, respectively.

The mean local densities of the two crossing flow scenarios are presented in figure 7.9. As expected, the density in the intersection is approximately twice that of the density in the corridors. In the low flow scenario, variations in the density are visible in the intersection area, while in the high flow scenario, the density is almost constant in the intersection area. We also see that the density starts building up several meters before the intersection area in the high flow scenario, indicating that the flow is near capacity in the intersection area.

Figure 7.8: Schematic map of the scenario which is denoted Crossing flow. Walkers created at O_A have D_A as destination and similarly for the pair O_B and D_B .

Figure 7.9: The local density in the high flow scenario (left), and the low flow scenario (right).

The mean discomfort density, presented in figure 7.10, has a similar distribution as the density. Note, however, that the discomfort is more than one order of magnitude smaller in the low flow scenario than in the high flow scenario. We notice a higher discomfort in the upstream corner of the intersection area, that is, in the south west corner. This is likely connected to the stripe formation phenomenon; in crossing flow stripes are formed of walkers walking in the same direction. In these stripes, walkers take cover diagonally behind and downstream of walkers in the same flow direction to minimize the interactions with walkers of the other flow. However, the leftmost walkers in the northbound flow, and rightmost walkers in the eastbound flow, has no one to take cover behind, so they are more exposed to the discomfort caused by the crossing flow. Thus, the local discomfort density is higher in the south west corner of the intersection area.

Figure 7.10: The discomfort density in the high flow scenario (left), and the low flow scenario (right).

The acceleration density, presented in figure 7.11, reveals another feature of the intersecting traffic scenario. A pronounced peak in the acceleration density is evident in the north east corner of the intersection area in the large flow scenario. Observations of the animations of the simulations reveal the cause of this peak; since the flow is so high, some walkers are having trouble crossing the intersecting flow and are swept along, causing them to reach the other side of the intersection at a point downstream of the corridor they are aiming for. Thus, they have to walk along the wall, opposing the intersecting flow, to round the corner. This of course implies extra acceleration. Another

way of expressing the same phenomenon is that it is easier to cross an intersecting flow with a smaller angle between direction of the intersecting flow and the walking direction, thus, the velocity of walkers get turned slightly in the direction of the intersecting flow.

Figure 7.11: The acceleration density in the high flow scenario (left), and the low flow scenario (right).

Both of the two phenomena mentioned above are also visible in the plots of the local delay rate densities, figure 7.12. The distribution is clearly skewed toward the south west corner of the intersection area, due to the dynamic stripe formation effect, and there is a peak at the north east corner.

There is yet another effect worth noticing in the delay rate density distribution. Downstream of the intersection area, that is, to the east and to the north of the intersection, there are areas with negative mean delay rate density. That is, on average, the walkers here have velocity components in the direction of their preferred velocities which are larger than their preferred speeds. This remarkable effect is due to that the walkers exiting the intersection area perceives a higher pressure from the high density in the intersection area than from the lower density in front of them. Interpreting this as a pedestrian behavior, this would mean that pedestrians are stressed by the situation in the crowded intersection area and hurry to escape from it.

To further investigate the interdependencies of the measures we compare the relation between the local density and each of the other measures. In figure 7.13 the discomfort density is plotted against the density. Here we clearly see the difference between the flows in terms of the amount of discomfort perceived by the walkers.

Figure 7.12: The delay rate density in the high flow scenario (left), and the low flow scenario (right).

Figure 7.13: The relation between the discomfort density and the density in the high flow scenario (left), and the low flow scenario (right).

The dependence of the acceleration density on the density is depicted in figure 7.14. As for the opposing flow scenarios in the previous section, the range of possible acceleration densities at a given density are larger than the range of possible discomfort densities. This is especially evident in the low flow scenario.

Figure 7.14: The relation between the acceleration density and the density in the high flow scenario (left), and the low flow scenario (right).

The plot of the delay rate density against the density in figure 7.15 shows that, for the high flow scenario, the amount of negative delay rate densities increases with increasing density, at least for low densities. However, at some point, above around 1 m^{-2} , the negative delay rate densities are getting less common, and above 2 m^{-2} there are hardly any negative delays, indicating that at these densities all walkers are moving slower due to the congestion, not just the quicker ones. These numbers are similar in both opposing flow scenarios.

In this section it has been demonstrated that the local measures can be used to obtain nontrivial properties of a pedestrian traffic scenario; both the drifting of walkers in the direction of the crossing flow and the areas with negative delay rate density were revealed by the measures.

Figure 7.15: The relation between the delay rate density and the density in the high flow scenario (left), and the low flow scenario (right).

7.2 Distribution of waiting pedestrians

In section 4.6, three extensions of the SFM to include waiting walkers were proposed. The implications of the three proposed waiting models were measured in terms of the delay caused by a group of waiting walkers; this delay was found to be significant and also differing between the models. Thus, it is important to choose the model that most accurately describes the real behavior of waiting pedestrians. However, to do this, it is preferable to measure quantities that are more directly observable than the delay. In this section the waiting models are compared by investigating the movements of the waiting walkers. By comparing the models in this way we demonstrate that the models produce behaviors that are easy to differentiate between through observations. This is achieved by considering the local density of the waiting walkers directly after the passing walkers have walked by, in both the experiment with 10 walkers and the one with 100 walkers. More precisely, we compare the replication average of the local density of the waiting pedestrians integrated over the length of the corridor resulting from simulations using the different waiting models. The comparisons are based on simulations of the scenario described in section 4.6. Each experiment is repeated 100 times and the comparisons are based on the average results.

First we compare the results of the three models in the scenario

with 10 walkers and 10 waiters. It is expected that when the PVM is used, many of the waiters will move out of the way of the passing walkers and end up along the walls of the corridor. When the waiters are controlled by the PPM on the other hand, their location should be practically unaffected by the passing walkers, since waiters described by this model always return to their preferred positions. The mass parameter of the APPM was chosen to $M = 4$ in this experiment, but the dependence of the behavior on the mass parameter is further examined later in this section. The density distribution resulting from the application of the APPM is expected to show some drifting, but not at all to the same extent as for the PVM.

Presented in figure 7.16 are the density distributions of waiting walkers across the corridor soon after the passage of the walkers. The average over the 100 repetitions are calculated in each point across the width of the corridor, and the standard error of the mean is everywhere less than or equal to 0.0042 m^{-1} , implying that the differences between the curves are not due to random effects.

Figure 7.16: The mean density of the 10 waiting walkers across the corridor after the 10 passing walkers have passed by. The mean is taken in each point over 100 repetitions of the simulation. The standard error of the mean is less than or equal to 0.0042 m^{-1} in all points. The mass parameter in the APPM is chosen to $M = 4$.

The plot of the local densities confirms our expectations; when the PVM is used to model the waiting behavior there are peaks in the density distribution close to the walls, when the PPM is used the distribution is more focused, and for the APPM the distribution is between those of the other two.

For a higher passing flow one should expect even more move-

ments of the waiters controlled by the PVM, and also significant movements of the waiters controlled by the APPM, since these waiters will adapt their preferred position more the longer time they are forced away from it. However, the distribution of waiters controlled by the PPM is expected to be independent of the passing flow. In figure 7.17, the results of the experiments involving 100 passing walkers are presented.

Figure 7.17: The mean density of the 10 waiting walkers across the corridor after the 100 passing walkers have passed by. The mean is taken in each point over 100 repetitions of the simulation. The standard error of the mean is less than or equal to 0.0102 m^{-1} in all points. The mass parameter in the APPM is chosen to $M = 4$.

As can be seen in the figure the distribution of waiters controlled by the PVM is similar to that of waiters controlled by the APPM, with most of the waiters concentrated along the walls of the corridors. The distribution of PPM waiters on the other hand, is almost unchanged compared to the experiment with 10 passing walkers. The standard error of the mean is less than or equal to 0.0102 m^{-1} in all points, implying that the difference between the distributions of waiters controlled by the PVM and the APPM in this experiment and the corresponding ones in the 10 passing walkers experiment is not likely due to chance.

These two experiments show that there are observable differences in the movements of the waiters controlled by the three models, both at a given flow, and in the dependence on the flow. This implies that observations of waiting pedestrians at the level of statistics of the local density can determine which of the models that best represents the behavior of waiting pedestrians in the observed situation.

So far we have only used one value of the mass parameter of the APPM. This parameter determines how easily the waiters adapt their preferred position and it have any value $M \geq 1$. Since the value of the parameter is hard to observe directly, it must be determined by a calibration procedure if the model is to be used. We now investigate the dependence of the distribution of waiters soon after the walkers have passed on the value of the parameter M , to determine the sensitivity of the model.

In figure 7.18 the results of simulations with four different values of M are presented. The results are from the experiment with 10 passing walkers. As can be seen in the figure the dependence of the distribution of waiting walkers on M is gradual; the distribution changes only slightly with each quadrupling of M .

Figure 7.18: The mean density of the 10 waiting walkers across the corridor after the 10 passing walkers have passed by in the APP model experiments. The mean is taken in each point over 100 repetitions of the simulation. The standard error of the mean is less than or equal to 0.0040 m^{-1} in all points.

As expected the distribution becomes more and more similar to the result of using the PPM as the value of the parameter is increased. This is expected since the APPM becomes identical to the PPM in the limit $M \rightarrow \infty$.

In figure 7.19 the same sequence of parameter values are used in the experiment with 100 passing walkers. Here we see a more sudden transition from a staying behavior to a moving behavior between $M = 16$ and $M = 4$.

In this section it has been shown that the differences between the three waiting models are significant in terms of the movements of

Figure 7.19: The mean density of the 10 waiting walkers across the corridor after the 100 passing walkers have passed by in the APPM experiments. The mean is taken in each point over 100 repetitions of the simulation. The standard error of the mean is less than or equal to 0.0105 m^{-1} in all points.

the waiting walkers. Furthermore, it has been shown that the dependence of the APPM on the value of the mass parameter, M , is not too strong.

7.3 Illustration of a realistic application

This section concludes the chapter with an illustration of the usage of the PTRS and the local measures on a realistically sized scenario. Here a railway platform is simulated to which two full trains arrive simultaneously, and all passengers alight. The simulated railway platform is an approximate representation of the platform between track 2 and track 3 at the railway station in Linköping in southern Sweden. The central part of the simulated scenario is depicted in figure 7.20, the rest of the platform is empty. The small squares along the edges of the platform are the alighting locations, that is, the doors of the trains, and the E shaped structures are the stairs down from the platform. The other structures are obstacles included in the simulation without any additional function.

The walkers are created stationary at the doors of the trains, and have as destinations the stairs down from the platform.

The trains that arrive at the platform have the same characteristics as the Swedish X2000 trains. The characteristics of the trains that are included in the simulation are the door configuration, that is, the

Figure 7.20: Schematic map of the central part of the simulated platform.

number and location of doors and their width, and the average and standard deviation of the alighting time, adopted from the work by Heinz (2003).

Figure 7.21, depicts the local density. The figure clearly reveals where the alighting walkers moves, and which areas of the platform that is hardly ever used. Also the local density reveals the congestion that appears in front of the stairs.

Figure 7.21: The density distribution obtained from the simulation of the Platform.

In figure 7.22 the acceleration density is given. Since the walkers are created at rest, a large part of the accelerations are performed at the train doors. The most pronounced peaks in the acceleration distribution are however in the congested area in front of the stairs, but there are also two small peaks to the right of the fourth pair of doors from the left. These peaks are due to walkers coming from the train doors further to the right who have to avoid the alighting walkers and the hexagonal obstacle.

When comparing the acceleration density in figure 7.22 to the discomfort density in figure 7.23, we see one of the most important differences between the two measures. While the acceleration density includes the acceleration performed by the walkers as they start walking, the discomfort density naturally does not include this.

Figure 7.22: The acceleration density distribution obtained from the simulation of the Platform.

Figure 7.23: The discomfort density distribution obtained from the simulation of the Platform.

Finally, in figure 7.24, the delay rate density is displayed. As expected, a large part of the delay is due to the starting acceleration of each walker, but also the congestion in front of the stairs. Again we note two small peaks at the fourth pair of doors due to the congestion in the narrow passages on both sides of the hexagonal obstacle.

Figure 7.24: The delay rate density distribution obtained from the simulation of the Platform.

This example shows that the measures reveal the structure of the traffic situation also in a realistically sized application. One possible application of a scenario like this could be to compare different designs of a platform. The simulations indicate that the hexagonal obstacle causes some delay and discomfort, so moving or removing it should be considered; of course after simulations of the alternative design have been performed.

Chapter 8

Discussion and future research

PEDESTRIAN traffic indeed exhibits many fascinating and complex phenomena. To be able to plan for efficient, comfortable, and safe pedestrian traffic a thorough understanding of these phenomena is important; we need to be able to predict the traffic in proposed pedestrian facilities, not just qualitatively, but also quantitatively. The research presented in this thesis has brought us some small steps in that direction, but there is still a long way to go before we have reliable, accurate, and efficient models of pedestrian traffic.

As summarized in chapter 1, the main contributions of this thesis are in addition to the literature reviews in chapters 2 and 3, the development of a documented SFM based simulation platform, the development of local measures of pedestrian traffic conditions, the demonstration of the importance of models of waiting pedestrians and the development and characterization of such models of waiting pedestrians.

In this chapter, these contributions will be discussed based on the assumptions underlying the methodology used, and in relation to the usefulness of the results, both in practical applications of pedestrian traffic simulation and in future research. Also, possible future research directions inspired by the work presented in this thesis will be discussed.

First, in section 8.1, the present and future capabilities of pedestrian traffic simulation are discussed. Then, in section 8.2, the question, related to the proposed local measures, of how we can and should quantify pedestrian traffic conditions is discussed. Finally in section 8.3, some aspects not touched upon in this thesis, but which would be interesting to study in future works, are discussed.

8.1 The capabilities of pedestrian simulation

How accurate are the state-of-the-art models of pedestrian traffic? This is a difficult question to answer, mainly for three reasons. First, it depends on the application: What kind of situation is modeled? Can the model handle all, or at least most, of the activities performed in the simulated area? If not, it is hard to give any accuracy measure at all. It is in this context that the assessment of the importance of including waiting behavior, and the development of such models, are important.

Second, it depends on how we characterize the pedestrian traffic situation, that is, what is measured. What we are interested in knowing should influence our choice of measure. The proposal of the local measures was induced by this issue. This question will be discussed in section 8.2.

Third, there are few detailed measurements of pedestrian traffic available. This is probably mainly due to the difficulties and cost associated with performing such measurements. But it may also be related to the lack of well defined and universally accepted measures of the traffic situation.

Fortunately the data collection problem is becoming less severe, since automatic detection of pedestrians from video data is developing rapidly. However, so far a large fraction of data collection projects on the microscopic level has been conducted in the form of controlled experiments, which of course has important advantages since much uncertainty can be eliminated. The contribution of such experiments to our understanding of the accuracy of the pedestrian traffic models, on the other hand, becomes limited. There are however some calibration experiments based on real pedestrian data, for example by A. Johansson (2009). However, the methodology used is based on comparison of individual trajectories, rather than measures at a more

aggregated scale of interest in applications. In addition to the microscopic calibration attempts there are some authors that approach the problem from the opposite end of the spectra, by comparing the results of the models to fundamental diagrams obtained from observations, see for example the work by Parisi et al. (2009). The ability of a microscopic model to reproduce known macroscopic relations is a minimal requirement, but should not be the only one since mesoscopic models have been demonstrated to successfully produce accurate traffic behavior at this level (Daamen, 2004). To obtain truly useful microscopic models the methods used to characterize traffic at a microscopic level must be improved, and more data collected. Thus, we have to conclude that the present accuracy of microscopic simulation models is to large extents unknown, but that the future looks promising with the advent of new data collection methods.

For the development of the waiting models, one of the basic assumptions was that the SFM is an accurate model of pedestrian dynamics. But if we are not sure of to which degree this is the case, or even what we should measure to determine it; can we still safely assume that this is indeed the case? We argue that even if the SFM is slightly inaccurate, the waiting models still have a value.

More precisely, the basic assumption underlying the development of the waiting models is that a force based model of pedestrian dynamics can be an accurate model, and that the preferred force is given by equation (3.1). This is a much weaker assumption than that the SFM is an accurate model of pedestrian traffic. The results may of course be slightly different for other force based models, or even for another set of parameter values of the SFM, but the waiting models are generally applicable for most force based models. The proposed models are obtained from some basic assumptions on the behavior of waiting pedestrians and requirements of simplicity, as described in sections 4.3 to 4.5. The resulting models are in one sense the simplest possible models with the assumed behaviors. To see this, consider the PPM. The basic assumption was that a waiting pedestrian has a preferred position at which it wished to stand. In a force based model, this implies an attractive potential with a minimum at the preferred position. By assuming that this potential is rotationally symmetric, a Taylor expansion gives the PPM. Thus, the PPM is in a very precise and conventional way a first approximation of a large class

of waiting models in a force based framework. In a similar way the APPM is a first approximation to a large class of waiting models with a dynamic preferred position. In this case, however, there is some freedom in the choice of the force affecting the preferred position, so the APPM is not as general as the PPM.

The development of the waiting models is important in several ways. First, it allowed us to estimate the importance of having an accurate model of waiting pedestrians. It also demonstrated that it is possible to extend the sFM in a natural way to include waiting pedestrians, and that this extension may be done in several ways. Even though all the proposed waiting models have some serious limitations, it seems reasonable that it should be possible to construct accurate models for most kinds of waiting behavior.

It should be noted that the proposed waiting models have drawbacks, the worst of which may be the assumption that the operational behavior of waiting pedestrians is well described by the sFM. This assumption was introduced to obtain a lower bound on the delay caused by waiting pedestrians on passing pedestrians, since waiting walkers controlled by the sFM will react strongly to passing pedestrians and move out of the way, thereby reducing the induced delay. This assumption will of course limit the applicability of the models. Some waiting pedestrians may move only marginally when other pedestrians pass by. This may be the case for example at interchange stations where some pedestrians may carry heavy luggage. However, it is reasonable that all pedestrians react to extreme situations in their surroundings. To achieve such behavior one possible approach could be to scale down the reactions of the waiting walkers. Such scaling can however lead to that the distance between walkers becomes too small, especially between waiting walkers. Another interesting possibility would be to introduce static friction for waiting walkers, causing them to be less inclined to react to their surroundings.

8.2 Quantifying pedestrian traffic conditions

As mentioned in section 8.1, one of the main challenges within the field of pedestrian modeling is the question of what to measure. This question is important for all aspects of the field, from how to actually observe real pedestrian traffic conditions, via model calibration, to

how to characterize the performance of a pedestrian facility. One of the main reasons that this is much more difficult than the corresponding question in vehicular traffic is that pedestrian traffic is a truly two-dimensional phenomenon.

Another reason is that the comfort of pedestrians may influence their behavior. In vehicular traffic the overtaking possibilities are limited, and the performance of the system can be measured in terms of easily observable quantities, such as queue length. Since vehicular traffic is almost always one-dimensional, the traffic is locally homogeneous; all vehicles travel in the same direction and with only small variations in preferred velocity. In pedestrian traffic it is much easier to overtake, resulting in a less ordered state which is more difficult to describe. There are, in general, no ordered queues that can be measured. Furthermore, the two-dimensional nature of pedestrian traffic makes the mean flow, which is one of the most important measures of vehicular traffic, less useful. Consider the crossing flows scenario in section 7.1.2; the mean flow in the intersection area is essentially the vector sum of the two individual flows, directed diagonally in a direction in which few pedestrians actually walk.

In vehicular traffic the ordered structure, and possibly the isolation of drivers from each other, imply that the discomfort is closely correlated to the efficiency, or rather, lack thereof. This means that the influence of the discomfort on the behavior of drivers is to large parts covered by the influence of delay. In pedestrian traffic, on the other hand, the discomfort induced by crowding may influence the behavior of pedestrians, even if the efficiency of the flow is only marginally affected. Thus, to characterize pedestrian flow, we must consider both its efficiency and the discomfort it causes.

The need for quantitative measures of the traffic situation originates from two related, but not identical, needs, the need to characterize and the need to evaluate the traffic situation.

The need to characterize the traffic situation is of course connected to calibration and validation of models. In this context, it is important that the data needed to calculate the measures is obtainable from observations, and that the measures capture features of the flow at a suitable level of detail. The measures should, on the one hand, not fluctuate too much, and should, on the other hand, not average out important features.

The need to evaluate the traffic situation puts other demands on the measures. In this case it is important that what is quantified by the measure represents something of value, that is, discomfort, delay or any other more general cost.

The above considerations motivate the development of the local measures proposed in this thesis. These measures characterize the traffic through the local density and the acceleration density, and allow evaluation of the traffic through the discomfort density and the delay rate density. The measures capture features of the traffic situation on a scale motivated by our understanding of pedestrian behavior. Features separated by distances longer than the typical interaction distance of pedestrians are resolved as separate features by the measures.

One limitation of the measures is that they are instantaneous. They can be integrated over time to give a time averaged value, but such averaging is manual and arbitrary. An interesting further development of the measures would be to include the distance in time between events in a similar way as the distance in space is handled in the presented measures. The problem of visualizing dynamic processes in an aggregated way without losing the dynamical information is of course a general problem, not specific for the proposed measures. This problem is more important in pedestrian traffic than in vehicular traffic because of the added dimension. The traffic dynamics of a highway segment can easily be visualized by a two-dimensional space-time diagram, but since all interesting pedestrian traffic situations are two-dimensional, the corresponding visualization becomes three-dimensional and hard to interpret.

8.3 Future research

The research presented in this thesis has focused on the operational level of pedestrian behavior, more precisely the SFM, making contributions to both our understanding of the model, and its capabilities. There is, however, more to pedestrian behavior than evasive maneuvers. This thesis has touched on the subject of route choice without actually exploring it. We have assumed that the route choice of the pedestrians is according to the shortest path, independent of the presence of other pedestrians. This assumption limits the validity of

the results, even though the scenarios have been chosen to minimize the effect of omitting deviations from this route choice behavior. The effects of including waiting pedestrians in the modeling of pedestrian traffic will depend on the route choice model used.

One interesting feature of the crossing flows scenario is the effect that some walkers drift in the direction of the crossing flow so much that they miss the opening on the other side and have to walk back along the wall. We do not have any data to confirm or reject that this is indeed an accurate description of pedestrian behavior. Clearly the predictions of this specific combination of the SFM and the shortest path route choice model needs to be compared to reality. Assuming that this is not a correct prediction, or at least that the effect is more pronounced in the simulations than in reality, one must ask whether it is a problem related to the SFM, to the route choice model, or to the way in which the models are combined. The route choice is represented in the model through the vector field describing the direction of the preferred velocity at each point. Since the SFM is connected to this field through the preferred force, a walker will not exactly follow the integral curves of this vector field if it is not constant, but will understeer. The effect may be related to the observed effect in the crossing flow scenario. Investigating the influence of the connection between the behavior at the operational level and the route choice model at the tactical level is an interesting line of future research.

The route choice of pedestrians poses many interesting questions, and we regard the problem of observations as the most important. Route choice is harder to observe automatically through video data than the operational behavior. One reason is that it takes place on a scale that is hard to cover with one camera. On the other hand, dynamic route choice will probably only affect the behavior of a pedestrian if it is able to *visually* determine that one route is better than another, that is, a camera should be able to capture all information that affects the choice.

Another interesting result of the simulations presented here is the significant amount of negative delays predicted by the model. Spontaneously, it feels reasonable to believe that some pedestrians with low preferred speed get stressed by faster surrounding traffic. Measuring the size of this effect is a significant challenge, due to the difficulties of observing the preferred speed of individuals in crowded

situations.

The assumption behind the estimate of the effect of including waiting walkers in the simulations was that the sFM is a reasonably accurate model of pedestrian traffic. The conclusion was that if a sFM based simulation framework is used, and there is waiting occurring in the simulated area, it is important to include waiting pedestrians in the model. The same approach can be used to evaluate the importance of each of the standard parts of the sFM; how important are the distribution of preferred speeds, the body force, the anisotropy of the interaction force, the random force, and so on. Some experiments in this direction were made by A. Johansson (2009), but more can be done.

This thesis has filled some gaps in our understanding of the sFM; with these gaps filled we can hope for a more efficient and accurate usage of the model. Related to this is an area of interesting and very important future research, the question of how to use models like the sFM in the best way. Should every pedestrian facility be simulated on this level of detail, or can we construct criteria for when it is necessary? At which level of detail should the model be calibrated, and which parameters can be assumed to not change from case to case?

Appendix A

Default parameter values of the PTSP

This appendix contains tables of parameters, in a broad sense, in the PTSP, and their default values. The references are to the source of the default values, a denotes A. Johansson (2009), and b, TRB (2010). The default distribution of preferred speeds are approximately adopted from a distribution of speeds of pedestrians crossing a signalized pedestrian crossing. A parenthesis in the value column indicates the interval of possible values.

Parameter name	Symbol	Value
Time step	dt	0.05 s
Cell size		0.1 m

Table A.1: Default values of parameters associated with the simulator object.

Parameter name	Symbol	Value	Ref.
Obstacle force strength	F_0^{OBST}	10 m s^{-2}	a
Obstacle force scale	σ^{OBST}	0.2 m	

Table A.2: Default values of parameters associated with the obstacle objects.

Parameter name	Sym.	Distr.	Value	Ref.
Preferred speed	v_i^p	$\mathcal{N}(1.37, 0.3)$	$(0.5, 2.25) \text{ m s}^{-1}$	b
Social force strength	F_0	const.	0.25 m s^{-2}	a
Walker radius	R_i	const.	0.15 m	
Max speed factor	γ	const.	1.2	
Force anisotropy	λ	const.	0	a
Look-ahead time	T_s	const.	1.27 s	a
Social force scale	σ	const.	0.59 m	a
Pref. force time scale	τ	const.	0.6 s	a
Random force	F^{RAND}	$\mathcal{N}(0, 0.1)$	$(-1, 1) \text{ m s}^{-2}$	
Phys. force strength	F_0^{PHYS}	const.	3 m s^{-2}	a
Phys. force scale	σ^{PHYS}	const.	0.2 m	

Table A.3: Default values of parameters associated with the walker objects.

Parameter name	Distr.	Value
Time gap distr.	$\mathcal{N}(2.3, 0.2)$	$(1, 10) \text{ s}$
Pos distr.	$\mathcal{U}(\text{within})$	(within)

Table A.4: Default values of parameters associated with the origin objects.

Parameter name	Distr.	Value
Wait time distr	$\mathcal{N}(30, 5)$	$(2, 30) \text{ s}$
Obst ext. dist	const.	0.4 m

Table A.5: Default values of parameters associated with the destination objects.

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Abbreviations

SFM Social Force Model

LOS Level of Service

PTSP Pedestrian Traffic Simulation Platform

CA Cellular Automata

PVM Preferred Velocity Model

PPM Preferred Position Model

APPM Adapting Preferred Position Model

QOS Quality of Service

ABM Agent Based Model

GUI Graphical User Interface

FMM Fast Marching Method