Methods for Modeling and Simulation of Multi-Destination Pedestrian Crowds

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Abstract. In this paper we present an overview of the four parts of a research project concerning pedestrian flow modeling. In retrospect, rapid growth in the volume of public transport in the last twenty years has urged efficient planning and optimal construction of public facilities. At the same time, the modeling of transport and pedestrian behaviors has become an important research topic as well. In the study of pedestrian behaviors, whereas evacuation scenarios (in which pedestrians all target a definite destination) and multi-agent systems (in which pedestrians are treated as heterogeneous individuals) have attracted much attention as two specific problems, comparatively little attention has been paid to pedestrian crowd behaviors in situations of multiple destinations. The objective of the present study is to investigate pedestrian behaviors in such a context. Our primary focus is the modeling of intersecting pedestrian streams. To address the problem from a practical perspective, we applied simple but realistic geometric configurations in our study, which could be independently extended, if necessary.

Keywords: microscopic, macroscopic and hybrid models, pedestrian density and flow measurement, kernel density estimation, human crowd experiments, intersecting pedestrian flows, MATSim extension

1 Simulation models

In the last years, several methodical approaches have been investigated for the modeling and the simulation of traffic problems. In the present context, we develop both microscopic approaches in which the pedestrian is considered as an individual in interaction with others, and macroscopic models in which the pedestrian behavior is analyzed in terms of more global properties of a continuous stream.

1.1 Microscopic models

In our project two microscopic models are developed. The first one is a grid-based approach relating to traditional cellular automaton (CA) models. The second is a combination of force-based and graph-based approaches.

Grid-based approach. The common grid-based approaches of the simulation of pedestrian dynamics assume and request that at any position represented by a grid cell there can be either exactly one pedestrian or none present. This implies that the grid cell associated with the aforesaid geometric position can be in a state of being empty (unoccupied) or occupied by a simulation participant (i.e. pedestrian). For this reason, the state change of the grid cell (i.e. position) is employed to describe the system dynamics of the simulation in the traditional CA model and its various extensions (see [1–7] and the references therein). The typical size of the grid cell was defined to be $0.4\text{m} \cdot 0.4\text{m}$ [1]. An important issue in these models is the update strategy. A proper update strategy is essential in the case of a high density of pedestrians in which multiple pedestrians simulated to enter into a same grid position can often be observed. In a straightforward manner, [2] introduced a (pseudo-)parallel update and the random sequential update for the simulation participants. The random sequential method involved further static and dynamic floor field information induced by the environment and pedestrians [1, 3, 7].

Our approach goes in a different direction. Our previous work [8] proposed a new solution for the step calculation in the general case of velocity larger than one grid cell size in one dimension per simulation cycle. (We therefore are of the opinion that is more suitable to categorize our approach as a graph-based method rather than a CA extension, since unlike in the case of step length 1, the immediate state dynamics, at least in the theoretical sense of cellular automata, become an issue of secondary significance. We are more concerned with the position evolution of the pedestrians in the simulation.) This method dissembles a step of $(\Delta x, \Delta y)$ (with Δx and Δy denoting integers of a suitable magnitude) into a a series of substeps which can be one grid cell in either direction or in both (i.e. a diagonal step). See Fig. 1. In this way, small deviations on route within a local

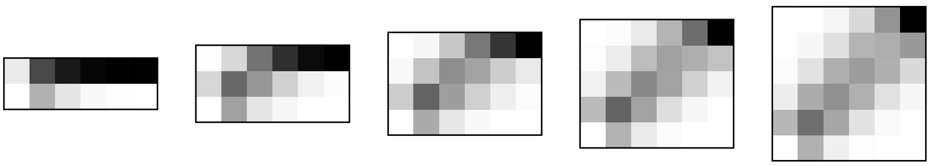


Fig. 1. Visual explanation of substeps with $\Delta x = 5$, $\Delta y = 2, \ldots, 6$. The frequency of cell position's occurrence in the substep choices is displayed in a gray scale. The start position $(0, 0)$ and the end position $(\Delta x, \Delta y)$ are by definition in white and black respectively.

step would become possible and strictly speaking, unavoidable. But these local deviations are all under the restriction that the mathematical expectation of the substep choices should be exactly equal to the position transition in geometric sense. This in addition enables the representation of heterogeneous pedestrians.

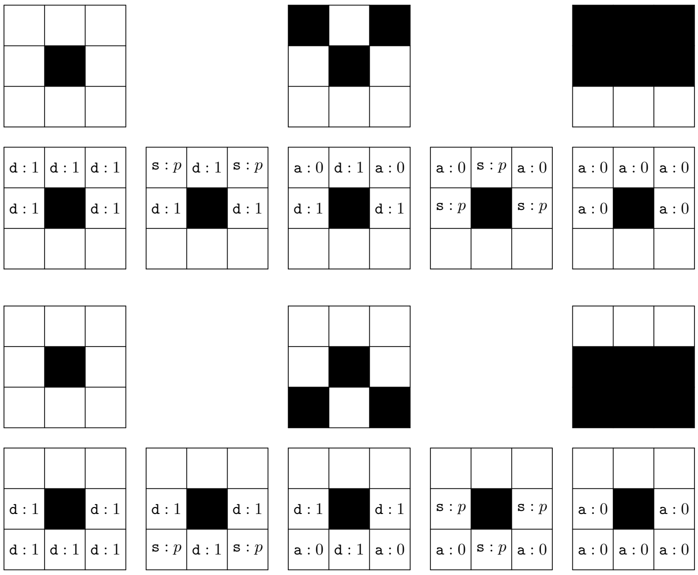


Fig. 2. Deactivation and activation of grid cells in the $3 \cdot 3$-Moore-neighborhood. The first two rows refer to the case for pedestrians with a different destination. The next two rows refer to the case for pedestrians with the same destination but as “follower”s. The current pedestrian is assumed to be moving in the positive y-direction.

In addition, we introduce a balancing mechanism in the simulation cycle to decide the execution sequence of the simulation participants. This improvement, along with the substep calculation, results in an enormous reduction of possible “dead-lock”s among the participants which should be addressed in the design of the simulation.

Another issue not to neglect is that, to our knowledge, the fixed grid cell size in the geometric setting poses a serious conceptual limit: the simulation participants (i.e. pedestrians) are all associated with a fixed spacial size, defined by the size of the grid cell in the model. Consequently, the pedestrians in the simulation have a fixed exclusive personal space, which is unfortunately not affirmed by empirical observations.

In our model this exclusive personal space is given additional attention. Naturally, we can reasonably assume the lower limit of this exclusive personal space to be the physical size of a typical real pedestrian (e.g. $0.3\text{m} \cdot 0.3\text{m}$) and the upper limit to be three times three of this base size (which implies that a real pedestrian enjoys an exclusive personal space of $0.9\mathrm{m} \cdot 0.9\mathrm{m}$ in the leisure state). Common sense and empirical observations confirm this. We can modify the personal space thus by defining some of the grid cells in the $3 \cdot 3$-Moore-neighborhood as unaccessible, we call this "deactivation" (abbr.: `d`). A grid cell definitely not to be deactivated is "activated" (abbr.: `a`). Any state between these two will be written as `s` and is associated with a probability number p for its deactivation.

In the context of multi-destination pedestrian dynamics then, a pedestrian tends to "deactivate" certain positions in his or her moving direction for those pedestrians with a different destination and in a similar way, this pedestrian "deactivate"s some of the positions for the "follower"s in behind, see Fig. 2.

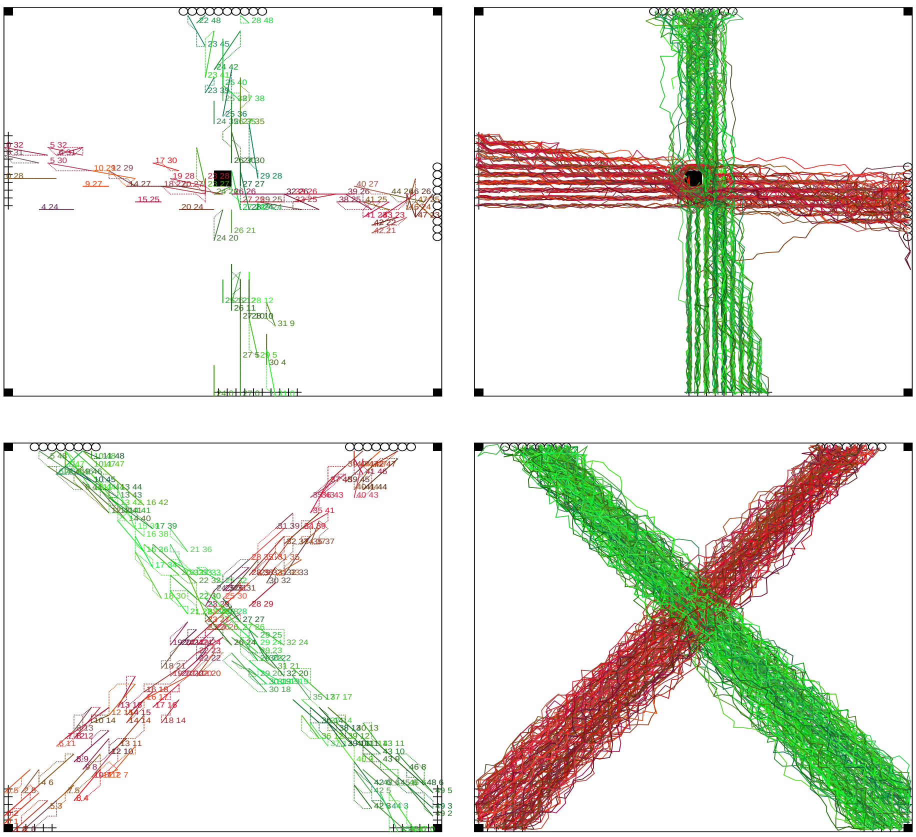


Fig. 3. The perpendicular intersection of two pedestrian groups.

p is defined as a linear function of the ratio of the temporary velocity to the upper limits in velocity. We list two simulation experiments in Figures 3 and 4.

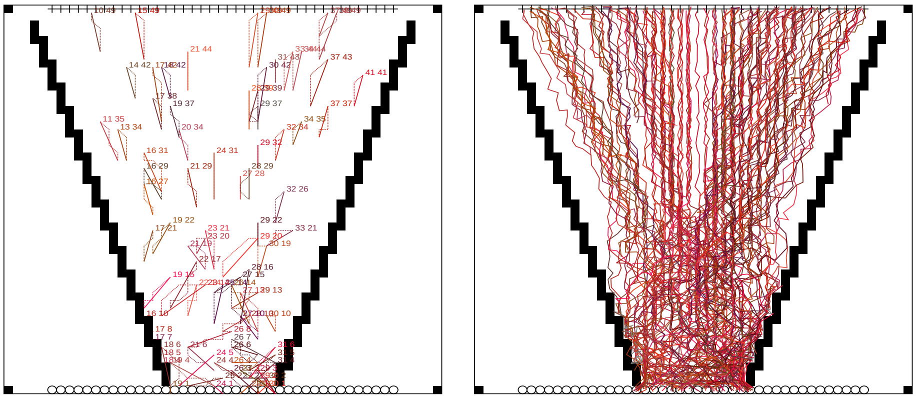


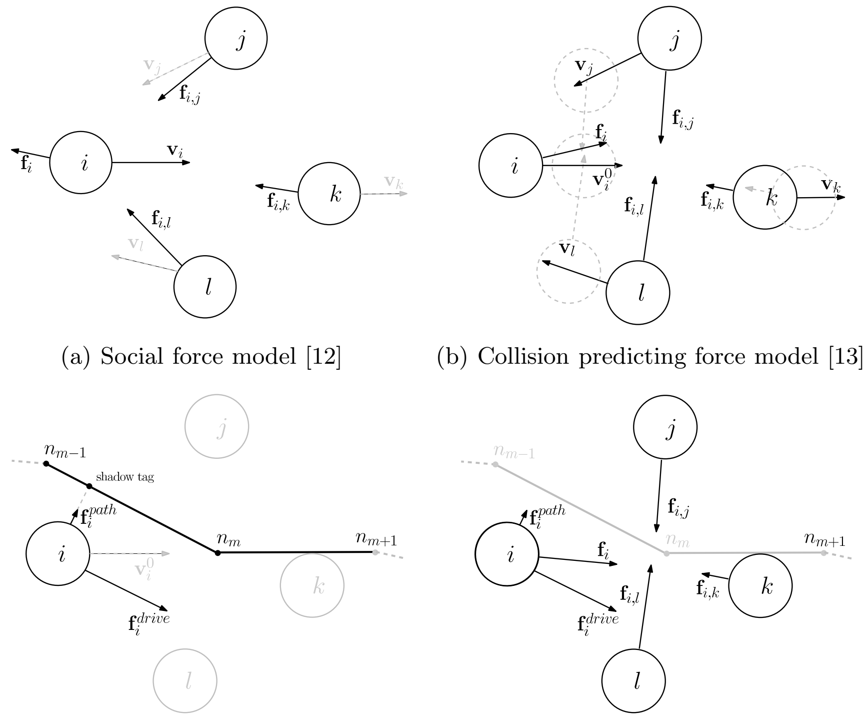
Fig. 4. A single group of pedestrians walking through a bottle-neck.

For a better visual effect, we will re-compile the results into video animation and publish them on our project home page.

Force-based approach. Force-based models employ discretized differential equations [9, 10] ("molecular dynamics (MD)") to compute the persons' movement. A well-known model using the MD analogy is the social force model introduced by [11]. In the social force model, each virtual person (agent) has a desired velocity towards a desired destination. While the simulation is running, agents try to adapt their velocity to the desired ones. However, a full adaption is usually not possible since the agents have to avoid other agents and obstacles. This interaction is modeled by repelling social forces emitted by obstacles and agents. These social forces depend only on the distances and not on actual velocities. An illustration of the social force model is given in Fig. 5(a). There are four agents in the scene depicted as circles i, j, k, and l. The figure demonstrates the force calculation from agent i's perspective. The agent has a desired velocity $\mathbf{v}_i^0$. The other agents are emitting repelling forces denoted by $f_{i,j}$, $f_{i,k}$, and $f_{i,l}$ respectively. The resulting force f_i is basically a linear combination of repelling forces and the desired velocity $\mathbf{v}_i^0$. (Details are given in [12].) It is shown that even agent i desires to move from left to right, the resulting force f_i exhibits a direction pointing to the left.

As has been shown that the model works particularly well in high density conditions, an example to name would be the evacuation scenarios in [12]. However, when dealing with pedestrian streams which possibly cross each other, it seems necessary to consider the velocities of the moving objects.

Another model that takes velocities into consideration in order to avoid collisions has been proposed by [13]. The basic idea of the model is to calculate potential collision points by projecting the actual scene into future under the assumption



(a) Social force model [12]

(b) Collision predicting force model [13]

(c) "Rubber strap" model for desired velocity calculation, proposed by [14]

(d) Combination of [13] and [14]

Fig. 5. Force-based models

of constant movement for all agents. The repelling forces are then calculated based on this projection instead of the current situation. The basic principle of this model is depicted in Fig. 5(b). The projected situation is indicated by dashed circles. The actual time to which the scene is projected depends on the individual times of closed approaches between agent i and agents j, k, and l. This approach leads, compared to the social force model, to a resulting force f_i that points in a complete different direction. In the example shown in Fig. 5(b), agent i is no longer pushed to the left, but instead the agent finds a way more or less in the direction of the desired velocity $\mathbf{v}_i^0$ by avoiding collisions at the same time.

Another issue which seems to puzzle the force-based models is the determination of the desired velocity vector. This is apparent, when it comes to complex way finding. Obviously it is possible to perform this on a graph. The actual route for an agent is then described by a list of links or nodes. A straightforward solution to combine this with a force-based model would be to let the desired velocity $\mathbf{v}^0$ point at the beginning towards the first node of the route and incrementally switch to the next node as soon as a node has passed. However, in [14] it is shown that such an approach leads to unrealistic behaviors when agents are moving next to each other. The reason is that those agents are pulled together when they approach a node and after the node is passed their trajectories diverge again. The authors propose a force system that follows the route in the navigation graph. The basic idea is that each agent keeps a shadow tag on the navigation graph, which moves along the graph as the agents move forward. The agents are connected by a virtual “rubber strap” to their corresponding shadow tag. They will be directed by a driving force that is parallel to the link where the shadow tag is present. The “rubber strap” pulls the agents towards the shadow tag when the distance to the link becomes too large. An illustration of this approach is given in Fig. 5(c).

In this project we propose a combination of the collision-avoiding model introduced by [13] and the “rubber strap” model [14]. Implementation details and first simulation results are discussed in [15].

1.2 Macroscopic models

The macroscopic approach is based on a set of pedestrian-specific coupled partial differential equations. These equations are not derived from the Euler or Navier-Stokes equations in fluid and gas dynamics. The specific situation of multi-destination pedestrian crowds as crossing streams requires the development of appropriately adapted methods. This has been targeted by means of simple heuristics.

Typical applications of these approaches include real-world scenarios like airports, shopping malls, buildings of middle to large size etc., where the participants (i.e. the pedestrians) do not exhibit an overall unanimity and may have different and multiple destinations.

Beyond the modeling techniques of the above-mentioned problems, a particular purpose of our work will be the development, implementation and test of appropriate computer-based simulation models. The assessment of the reliability of these models by a comparison with real data obtained from experiments of intersecting pedestrian groups is currently in progress.

Model equations. Starting from the mass balance for species mixture for every species, the continuity equations

$$\frac{\partial \rho_i}{\partial \vartheta} + \nabla \cdot (\rho_i v_i) = 0 \tag{1}$$

will be considered. For the velocities of pedestrian group i, the following formulation

$$v_i = a_i V d_i^{\mathrm{i}} - b_i (1 - V) d^{\mathrm{l}} \tag{2}$$

is applied. A detailed discussion of the model is carried out in [16]. Here we will explain the essentials briefly. $V = V(\rho)$ stands for the velocity magnitude from a suitable velocity-density diagram where $\rho = \sum \rho_i$ is the sum of the species densities. To incorporate non-local effects on the pedestrian dynamics, we map the non-attracting spots like walls, obstacles and jams to potentials by solving a set of potential equations. These potentials are used to define the vector fields d_i^{i} and d^{l} which de-accelerate or accelerate the pedestrian movement. Also in (2), a_i, b_i are constants configured from the resulted numerical tests in comparison with the data acquired from experiments.

Some aspects for setting boundary conditions. Boundary conditions usually comprise the entries and exits of a certain region to be simulated. The fact that pedestrians are "sensitive" in their decision-making concerning spacing configurations should draw our attention. With consideration of the fact that information applied on boundaries, to a large extent, cannot be derived from the model, certain assumptions must be made. An example would be that on the boundary representing a wall, it is obvious that pedestrians are not allowed to move through it. This means that the flux through the corresponding wall is zero. In the flux part of (1), the condition of either $\nu \cdot v_i = 0$ or $\rho_i = 0$, as well as both simultaneously, is sufficient to guarantee this behavior.

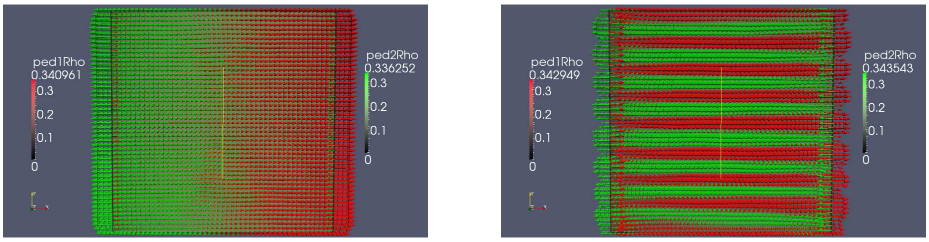


Fig. 6. Simulation of two pedestrian groups which walk in opposite directions.

An elaborate discussion of modeling in combination with different boundary constellations is detailed in [16].

2 Experiments and real world data generation

The evaluation of simulation models requires reliable and clearly defined empirical data. These empirical data may be obtained from either naturally occurring human crowds [17] or pedestrian flows that have been produced under controlled, experimental conditions [18–20]. In general, such experiments are designed to demonstrate crowd behavior in special situations such as evacuation or passing through a bottleneck or corridor.

In our case, for the access of reliable empirical data of intersecting pedestrian flows of multiple destinations, we conducted in 2010 human crowd experiments at Technische Universität Berlin.
The spatio-temporal positions of the pedestrians were obtained via photogrammetric means from video data recorded with multiple temporally synchronized network surveillance video cameras. Tracking of the pedestrians was facilitated with the Lucas–Kanade algorithm. Smooth trajectories were then obtained via approximation with cubic B-splines, and the combinatorial assignment of trajectories obtained from different camera perspectives was supported by the Kuhn–Munkres algorithm. Finally, we computed dynamic local density and flow fields via a novel method based on variable-bandwidth nearest-neighbor kernel density estimation.

In the following, we will quickly summarize the experimental setup and the methodology for the computation of trajectories and density/flow fields from the recorded video data. For more details, we refer to [21–23].

2.1 Experimental setup

During the Lange Nacht der Wissenschaften 2010 (Long Night of the Sciences) four volunteer groups of event visitors were instructed to move from opposite sides of an observation area located in the entrance hall of the Department of Mathematics of Technische Universität Berlin, to create various scenarios: two groups and four groups intersecting from perpendicular directions, two groups meeting head-on, and two groups meeting head-on from an angle of approximately 180 degrees.

In a follow-up experiment later that year, under similar conditions, two pedestrian groups (a group composed of 142 subjects and another with 83 subjects) intersected at an angle of roughly 90 degrees for one minute in a region of about twenty-five square meters, reaching a peak density of about five pedestrians per square meter. In our studies, we use this experiment as the main test case. The scene was recorded from a gallery at a height of about six meters with five networked and temporally synchronized JVC VN-V25U surveillance video cameras. We analyzed the data provided by the three central cameras which covered the area where the two pedestrian groups meet, see Fig. 7. A particular challenge concerning the photogrammetric analysis was manifested by the fact that due to constructional limitations of the building the scene could not be captured from a bird's eye view.

2.2 Extraction of trajectories

After measurement of the world and image coordinates of about 30 reference points in the scene, the cameras were calibrated under the assumption of a pinhole model. Then, for each video frame, the heads of the pedestrians were marked manually, aided by the Lucas–Kanade tracking algorithm [24, 25]. In the next

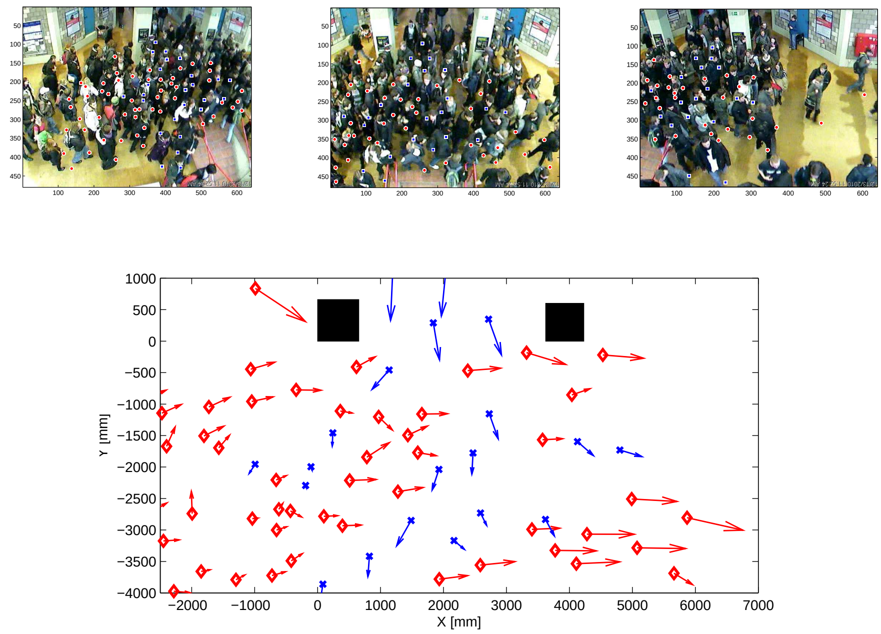
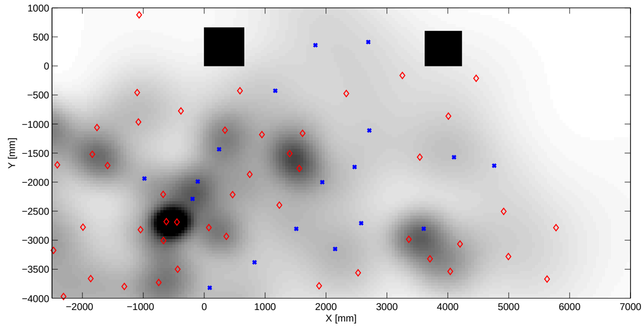


Fig. 7. Video snapshots of intersecting pedestrian groups and the retrieved positions and local velocities of the subjects. The figures (snapshots) in the first row are measured in pixel elements delivered by hardware, whereas in the overall computed result (second row) length is measured in physical unit. The conversion is not linear, for details consult the references mentioned in the text.

step, we marked the floor position of each pedestrian in (at least) one frame in order to compute the height of the respective pedestrian via the homography determined from camera calibration. Given this information, the world coordinates of the pedestrians' floor positions can be computed for each frame. These spatio-temporal positions were then approximated with cubic B-splines in order to obtain smooth trajectories. Finally, the trajectories extracted from different camera perspectives were brought together by combinatorial assignment with the Kuhn–Munkres algorithm [26, 27].

2.3 Local density and flow fields

We are of the opinion that dynamic local density and flow fields as a representation of pedestrian dynamics are particularly suited for the calibration and validation of a variety of models: macroscopic simulations already produce density and flow fields, and data obtained from experiments or microscopic simulations may be converted into such fields.



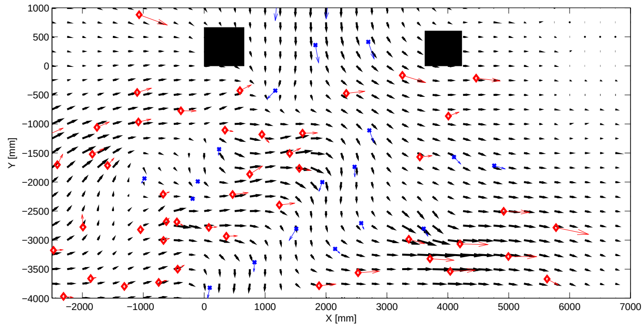


Fig. 8. Pedestrian density and flow fields at a fixed point in time. The blue and red arrows indicate the velocities of individual pedestrians.

In order to compute density and flow fields from pedestrian trajectories, we propose a new method based on a particular variable-bandwidth kernel estimator. Other feasible techniques include the Voronoi method [28] or kernel estimators with fixed bandwidth [17]. The bandwidth is defined in such a way that it decreases with the number of pedestrians located in the close vicinity and their respective distance. Therefore, this method supports a description of the limited range of pedestrians in particularly crowded situations. For details of the algorithm we refer to [21]. In Fig. 8, the density and flow fields are shown for the situation illustrated in Fig. 7.

3 Hybrid ansatzes

Merging the advantages of the respective microscopic and macroscopic models is a long-term objective of the present project. One possibility consists in the

Table 1. Incompatible model features of macroscopic models and MATSim and adaptation approaches

MATSim	Macroscopic model	Adaptation approach
geometry data consists of obstacles; paths are followed on graphs of intended routes	need for a meshed bounded area with flux-conditions at the boundaries; intended walking directions should be provided for every point in the computational domain	cutting part of the plane used in MATSim of a subproblem, provide it with (inner and outer) boundaries and mesh it; generate a field of intended directions in the domain
traceable agents moving on planes according to certain rules	densities of pedestrian species are subject to transport equations modeling the "interaction" of pedestrians perceived as unstructured "matter"	providing an interface to convert moving agents into densities and/or fluxes of "matter", which can be considered consisting of groups of agents that are equivalent in the context, at the inflow boundaries; "re-assemble" the agents at the outflow boundaries of the macroscopic model based on thresholds and FIFO lists

exploitation of the potentials generated in the macroscopic modeling to qualify the decision-making of the agents in the microscopic model not to be oversimplified. In this field, first results have been obtained and an implementation of such a model modification is feasible.

On the other hand, it is possible to employ the velocity and density fields as results of the macroscopic mathematical model in a straightforward manner to reconstruct paths of members of a pedestrian group. But unfortunately, in general, compatibility among agent-based models—as we have seen them integrated in our MATSim modeling—and macroscopic models cannot be guaranteed. The integration of macroscopic models into the framework MATSim has thus been our concern in the current project.

The techniques to adapt the data to provide the information flux between the models have been listed in Tab. 1. The macroscopic model applied has also been shown as an integrated module of MATSim, the implementation of which has been carried out in the OpenFOAM framework by providing a simulation utility that has to be run in a so-called case directory holding the necessary initial and control information of the setting which is be simulated. Thus the interaction of

MATSim with the macroscopic model solver is in a master-slave-state. MATSim, as the master, generates the case directory structure, calls the simulator and re-extracts and converts the data from the slave, that is, the macroscopic model, in a form needed for further computation.

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References

1. Burstedde, C., Klauck, K., Schadschneider, A., Zittartz, J.: Simulation of pedestrian dynamics using a two-dimensional cellular automaton. Physica A **295** (2001) 507–525
2. Keßel, A., Klüpfel, H., Wahle, J., Schreckenberg, M. [29] 193–200
3. Schadschneider, A. [29] 75–85
4. Kirchner, A., Nishinari, K., Schadschneider, A.: Friction effects and clogging in a cellular automaton model for pedestrian dynamics. Physical Review E **67**(5) (2003) 056122
5. Klüpfel, H.L.: A cellular automaton model for crowd movement and egress simulation. PhD thesis, Universität Duisburg-Essen (2003)
6. Kirchner, A., Klüpfel, H., Nishinari, K., Schadschneider, A., Schreckenberg, M.: Discretization effects and the influence of walking speed in cellular automata models for pedestrians dynamics. Journal of Statistical Mechanics: Theory and Experiment **2004**(10) (2004) P10011
7. Nishinari, K., Kirchner, A., Namazi, A., Schadschneider, A.: Extended floor field CA model for evacuation dynamics. IEICE Trans. Inf. & Syst. **E87-D**(3) (2004) 726–732
8. Chen, M.J., Bärwolff, G., Schwandt, H.: A study of step calculations in traffic cellular automaton models. In: 13th International IEEE Conference on Intelligent Transportation Systems. (2010) 747–752 An electronic version can be retrieved at: `http://page.math.tu-berlin.de/~chenmin/pub/cbs100709.pdf` (accessed May 11, 2012).
9. Helbing, D., Farkas, I.J., P.Molnár, Vicsek, T. [29] 21–58
10. Helbing, D., Buzna, L., Johansson, A., Werner, T.: Self-organized pedestrian crowd dynamics: Experiments, simulations and design solutions. Transportation Science **39** (February 2005) 1–24
11. Helbing, D., Molnár, P.: Social force model for pedestrian dynamics. Phys. Rev. E **51** (May 1995) 4282–4286
12. Helbing, D., Farkas, I., Vicsek, T.: Simulating dynamical features of escape panic. Nature **407** (2000) 487–490

13. Zanlungo, F., Ikeda, T., Kanda, T.: Social force model with explicit collision prediction. EPL (Europhysics Letters) **93** (2011) 68005
14. Gloor, C., Mauron, L., Nagel, K.: A pedestrian simulation for hiking in the alps. In: Proceedings of the Swiss Transport Conference (STRC). (2003)
15. Lämmel, G., Plaue, M.: Getting out of the way: Collision avoiding pedestrian models compared to the real world. (2012) to appear in the same volume.
16. Huth, F., Bärwolff, G., Schwandt, H.: A macroscopic multiple species pedestrian flow model. (2012) to appear in the same volume.
17. Helbing, D., Johansson, A., Al-Abideen, H.Z.: Dynamics of crowd disasters: An empirical study. Physical Review E **75** (2007) 046109
18. Daamen, W., Hoogendoorn, S.P.: Experimental research on pedestrian walking behavior. In: Transportation Research Board annual meeting. (2003) 1–16
19. Galea, E.R., Filippidis, L., Wang, Z., Lawrence, P.J., Ewer, J.: Evacuation analysis of 1000+ seat blended wing body aircraft configurations: Computer simulations and full-scale evacuation experiment. In: Proc. PED2010. (2011)
20. Zhang, J., Klingsch, W., Schadschneider, A., Seyfried, A.: Transitions in pedestrian fundamental diagrams of straight corridors and T-junctions. J. Stat. Mech. (2011) P06004
21. Plaue, M., Bärwolff, G., Schwandt, H.: On measuring pedestrian density and flow fields in dense as well as sparse crowds. (2012) to appear in the same volume.
22. Plaue, M., Chen, M., Bärwolff, G., Schwandt, H.: Multi-view extraction of dynamic pedestrian density fields. preprint (2012)
23. Plaue, M., Chen, M., Bärwolff, G., Schwandt, H.: Trajectory extraction and density analysis of intersecting pedestrian flows from video recordings. In: Proc. PIA11. Volume 6952 of LNCS. (2011) 285–296
24. Lucas, B.D., Kanade, T.: An iterative image registration technique with an application to stereo vision. In: Proc. of Imaging Understanding Workshop. (1981)
25. Shi, J., Tomasi, C.: Good features to track. In: Proc. of the IEEE Comp. Soc. Conf. on Computer Vision and Pattern Recognition. (1994) 593–600
26. Kuhn, H.W.: The Hungarian method for the assignment problem. Naval Research Logistic Quaterly **2** (1955) 83–97
27. Munkres, J.: Algorithms for the assignment and transportation problems. Journal of the Society for Industrial and Applied Mathematics **5**(1) (1957) 32–38
28. Steffen, B., Seyfried, A.: Methods for measuring pedestrian density, flow, speed and direction with minimal scatter. Physica A **389**(9) (2010) 1902–1910
29. Schreckenberg, M., Sharma, S.D., eds.: Pedestrian and Evacuation Dynamics. Springer-Verlag Berlin Heidelberg (2002)