A Methodological Approach to Adjustment of Pedestrian Simulations to Live Scenarios: Example of a German Railway Station

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Abstract Pedestrian stream simulations serve to predict the flow of a crowd. Applications range from planning safer buildings, performing risk analysis for public events to evaluating the clever placement of advertisement. The usability of a simulator depends on how well it reproduces real behavior. Unfortunately very little data from live scenarios has been available so far to compare simulations to. Calibration attempts have relied on literature values or, at best, laboratory measurements. This paper is based on live video observations at a major German railway station. We present a methodological approach to extract key data from the videos so that calibration of the simulation tool against live video observations becomes possible. The success of the approach is demonstrated by reproducing the real scenario in a benchmark simulator and comparing the simulation with the live video observations.

1 Introduction

Real time simulations of pedestrian behavior collect live data and calibrate the simulator against the actual scenario. After that predictions on the evolution of the scenario are made. For a useful prediction it is essential that the simulator is capable of reproducing real situations. An accurate reproduction of known data, without being an exact proof, indicates that the simulator may be trusted. This is best tested beforehand by comparing simulation data to data that was extracted from live observations and stored.

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Unfortunately such live data is not readily available and most calibration attempts are still based on literature data or laboratory experiments. They focus on some specific phenomenon, such as the reproduction of the classic fundamental diagram by Weidmann [1] and Schadschneider et al. [2]. This is very helpful and fully justified when one seeks to better understand an isolated phenomenon. However, one cannot expect to reproduce a complete scenario with all the aspects that define this scenario. For this a more holistic attempt is necessary. The authors are not aware of any publications on comprehensive calibration.

In this paper we use data gathered through video cameras installed at a major German railway station to demonstrate step by step, how data collection, data analysis and calibration of simulation against data from live scenario are combined to ensure high quality predictions of pedestrian flows.

The results also shed some more light on to which extent the use of the classic literature values on density-flow relationships compiled in [1] is adequate to calibrate the scenario we investigate. In particular, we look at the free-flow velocities of pedestrians and the fundamental diagram. We finally demonstrate the success of the proposed methodology: We apply it to a one of our sample videos. Then we feed the results into a benchmark pedestrian stream simulator and compare the evolution of the density of the simulation experiment to the measurements in several observation areas.

2 Gathering Data for a Scenario: A German Railway Station

Several cameras filmed the crowd flow in a part of a German railway station from the bird's view. The trajectories of individual pedestrians in time and space must be extracted manually from the videos using a tool that allows to "click" positions on the video. At this point we have finished analyzing two of the videos, each of which has a duration of at least 1.5 min. The number of pedestrians walking on each video is about 400 persons. The area covered on each video includes several platforms and a part of the station's main hall.

All trajectories within the complete area of video observation were extracted and analyzed. Some trajectories are partially obscured from the camera view or the view is distorted by distance. Obscured or distorted trajectories are only used to gather source-target statistics. The detailed analysis of velocities and flows is conducted exclusively on the visible and undistorted parts of the trajectories to keep measurement errors small. Figure 1 shows a schematic picture of an area of observation of a measurement experiment, highlighting the fact that one has to deal with hidden areas.

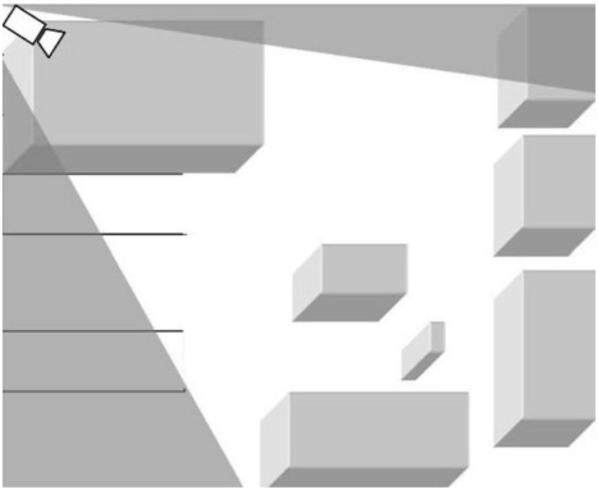

Fig. 1 Schematic representation of the measurement experiment: The *white area* corresponds to the field of vision of a camera mounted at a location in the *upper left* corner of the picture. There are platforms on the *left*, obstacles in the *middle* and a wall on the *right side*

3 The Benchmark Simulation Tool

There are many different models for pedestrian movements, all of them having their own merits. For surveys we refer to [3–7] with descriptions of a large number of approaches for modeling pedestrian movements.

Our own simulation tool is a cellular automaton. The simulator has been described in earlier publications by the authors and by their colleagues, namely in [8]. Details on calibration according to fundamenatal diagrams are given in [9] and the path finding method based on geodesics is described in [10, 11]. We will therefore restrict the description to the minimum necessary to understand the paper.

In a cellular automaton the area of observation is divided in a lattice of cells. Each cell at each time step has a status: either empty or occupied by either a person, or an obstacle, or a source or a target. Virtual persons enter and leave the scenario through sources and targets. The cells are updated by rules which together form the automaton. The cell diameter is usually set to 53 cm to accommodate an average sized European male (Fig. 2).

The core of the model is contained in the automaton, that is, the set of rules according to which the cell states are updated when the simulation steps forward in time. In many aspects, the model is similar to other cellular automaton models based on potentials [2, 12–15].

We imagine that attractive forces act between targets and pedestrians, whereas obstacles and other pedestrians repulse pedestrians. These forces between pedestrians, targets and obstacles are expressed through suitable scalar functions: the

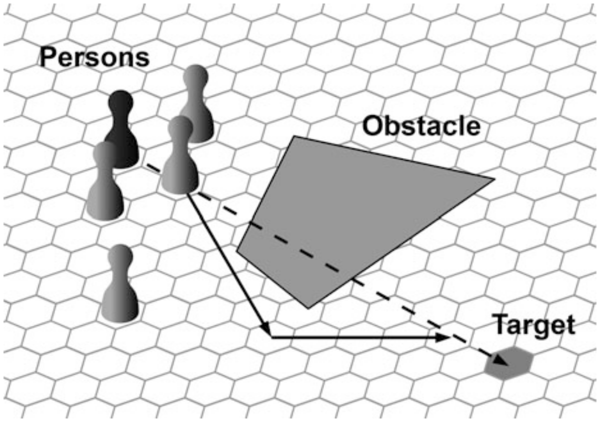

Fig. 2 Pedestrians move on a grid with hexagonal cells towards a target. Persons, targets and obstacles occupy cells. Positions are updated sequentially in each simulation step, so that collision is impossible

potentials. Virtual persons seek to minimize the overall potential when stepping ahead. Obstacles are successfully skirted because the target potential is given through the arrival time of a traveling wave front [10]. A sequential update scheme makes collisions impossible. Furthermore, each person has an individual speed that the person tries to achieve – and indeed does achieve when the path is free: the free-flow velocity. Our model enriches the basic ideas by a number of sub-models to compensate the most relevant shortcomings [8].

4 Methodology: Realistic Calibration According to Video Data

The next step is to adjust the simulations to video data. In order to achieve this, we need to define sets of data and parameters that capture the most important phenomena. Some data, such as the location and form of obstacles, is extracted from the videos and then directly fed into the simulation. We also extract parameter estimates by statistically analysing the data. For some parameters, we may also need to find statistical distributions. This is the case for the free-flow velocity, where literature suggests a normal distribution [1]. In some cases, we may have to measure a dependency instead of a simple parameter, such as the relationship between density and velocity or equivalently density and flow in a crowd.

We propose to extract the following information, which we consider necessary for the reconstruction of live scenarios, from the video footage and, if available, floor plans. We would like to stress that in some scenarios additional input, like the average size of pedestrians, may be necessary or at least beneficial.

- **The topology of the area of interest** in two dimensions. This is direct input data.
- **The positions of sources and targets within a scenario**, that is, the locations where people come from and to where they go to. This is again direct input data.
- **Statistical information on the distribution of trajectories between sources and targets.** This data is necessary to direct virtual pedestrians from sources to targets in a way that fits the scenario.
- **A schedule of pedestrian appearances and disappearances.** How many persons per second appear or disappear at each location? This data is necessary to feed virtual pedestrians into the simulation so that it fits the scenario and to adequately remove them from the simulation.
- **The scenario specific distributions of free-flow velocities**.
  It is very important to use the measured free-flow velocity distribution that is correct for a particular scenario. Only then our simulation will produce consistent and quantitatively correct data: e.g. during the rush hour we observe mostly fit walkers with a clear purpose in mind. They tend to walk fast towards their goals. Only minutes later, when the last commuter train has arrived and its passengers have left the station, we may observe a more relaxed crowd of casually strolling tourists with no particular goal or time schedule in mind.

  At 17:26 p.m. we measured a mean free-flow velocity of 1.04 m/s with a standard deviation of 0.51 m/s at the railway station. This differs significantly from the benchmark data for a Gaussian distribution about a mean of 1.34 m/s with a standard deviation 0.26 m/s in [1]. The histogram and quantile plot of the measured distributiona are depicted in Fig. 3 and in Fig. 4. In the benchmark simulations presented in Sect. 5 we decided to use a normal distribution with the mean and standard deviation from the data including some very slow and very fast pedestrians.
- **Measured data from which the density-flow relationship (fundamental diagram) valid for the current scenario can be derived.** The density-flow relationship observed in the video also deviates from the fundamental diagram provided by Weidmann (see Fig. 5). The method to calibrate the pedestrian simulation against a given density-flow relationship that we use in the benchmark simulator is described in detail in [9].

5 Results

As soon as the steps from Sect. 4 are completed and the adjustments against measured data have been performed, a comparative simulation can be started. We compare simulation results and video measurements for data that was recorded during the rush hour in the afternoon. In the benchmark scenarios a train arrives on a platform (on the left side of Fig. 1), passengers exit the train and move to different destinations, such as the entrances to the subway, food stalls, elevators and other platforms. Accordingly, the density is low at first. Then the bulk of the passengers appear on the video and a higher pedestrian density is measured.

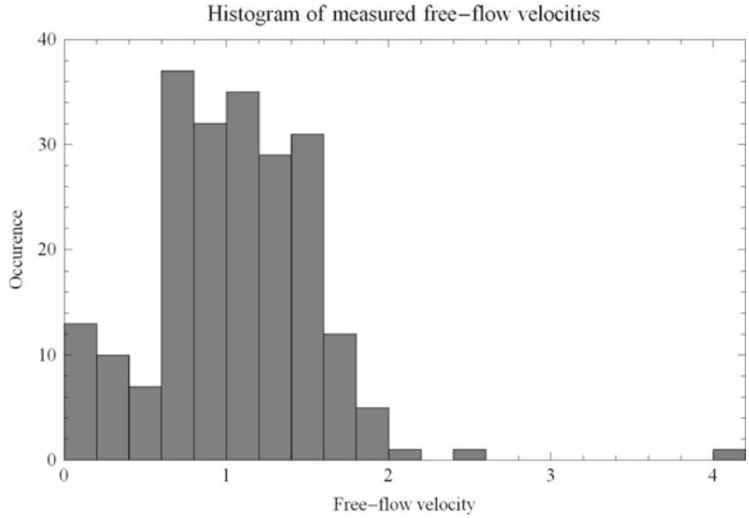

Fig. 3 Histogram of free-flow velocities at 17:26 p.m. at a German railway station. Only the 214 trajectories with a free path in the direction of movement are considered. The mean free-flow velocity is 1.04 m/s and the standard deviation is 0.51 m/s

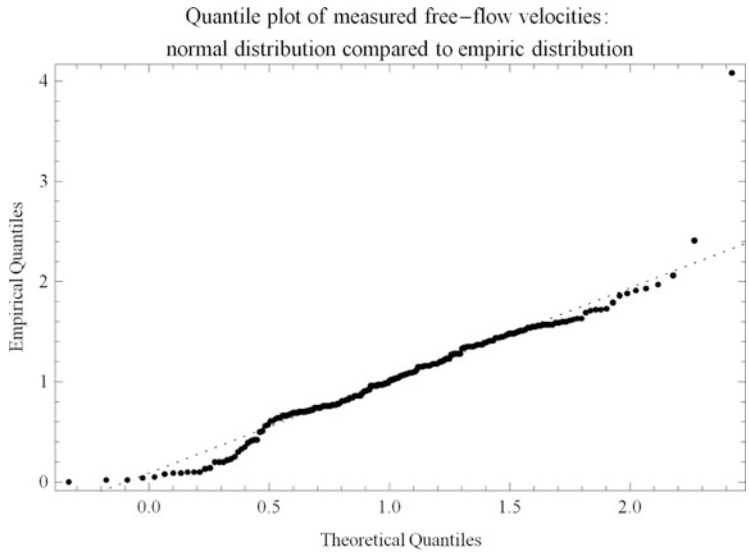

Fig. 4 Quantile plot of free-flow velocities comparing the distribution of the free-flow velocities measured at 17:26 p.m. at a German railway station to a normal distribution. Only the 214 trajectories with a free path in the direction of movement were considered

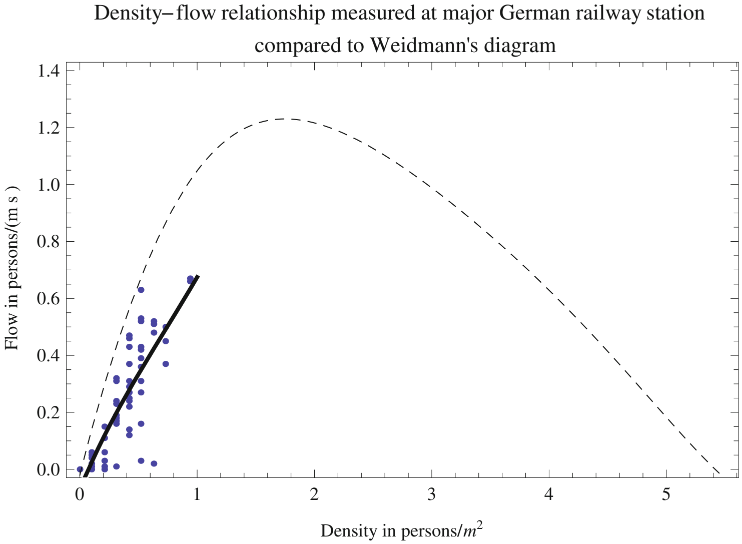

Fig. 5 Measured density-flow relationship at a German railway station at 17:26 p.m. on a workday compared to Weidmann's diagram (*dashed line*). Densities above 1 person/m^2 did not occur. The *solid line* is a smooth approximation of the measured data

Finally, the pedestrian density decreases slowly. After 3 min no more passengers come from the platform. Only pedestrians that come from other trains or entrances are seen in the main hall.

When comparing measurements to simulation results one must find suitable quantities that allow such a comparison. The sources, destinations and speeds of the virtual pedestrians in our simulations match measurements statistically, that is, the distributions coincide. Individually no such match can be expected and, as a consequence, individual trajectories cannot be compared. We need an aggregated quantity instead. We pick the density of the crowd as it evolves with time in an area of observation. The density cannot only be measured quite easily in both cases, but is also of immediate interest, because densities above a certain threshold would be an indicator for impending danger.

Figure 6 shows a comparison of simulated and measured densities in a time span of 3 min. Solid lines correspond to the video footage, dashed lines to the simulation. The prediction from the simulator qualitatively reproduces the scenario quite well, that is, the peak density occurs in the area of observation, at the correct time, for the correct duration and in the correct order of magnitude.

However, the result somewhat overestimates the densities. Part of the differences can be explained by the influence of chance. The simulation is subject to random input as far as the velocities of the virtual pedestrians and their chosen trajectories are concerned. Only the distributions of the input and measurement parameters coincide. Therefore, for each new seed and for each new simulation the results differ and one cannot ever expect a complete match with the measurements.

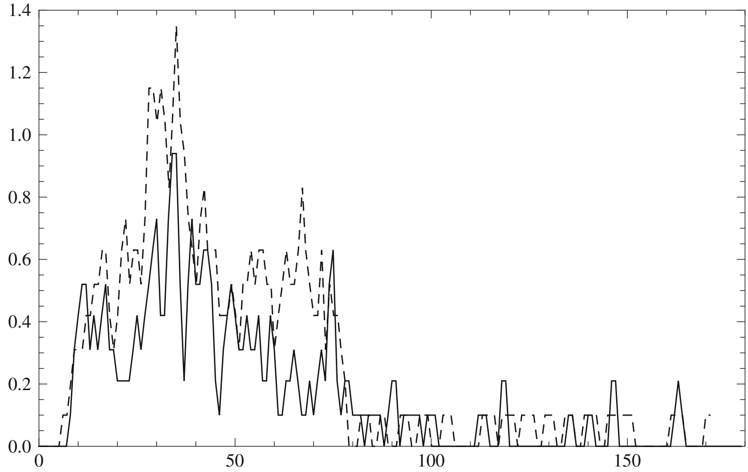

Fig. 6 Comparison of measured densities from video footage (*solid line*) and simulated densities (*dashed lines*) when pedestrians are fed into the scenario with the source target distribution, the free-flow velocities and the density-flow relationship measured at the start of the scenario. One hundred eighty seconds (3 min) are simulated

We also suspect that the real pedestrians coordinate their movements better than the virtual pedestrians. The virtual pedestrians are quite 'short sighted' and take steps to avoid collision only when the actually 'feel' the potential of the other pedestrians. Real pedestrians are more likely to plan ahead. This is a typical disadvantage of high speed pedestrian stream simulators that need to restrict influences to a near field, so-called greedy algorithms, to keep computation times low.

The important question is whether this systematic overestimation is acceptable. In our case, we are interested in a warning system for potentially dangerous densities. Therefore we believe that slight overestimates can be tolerated, whereas underestimations would be inacceptable.

6 Discussion and Next Steps

In this paper, we proposed a methodological approach to adjust pedestrian simulations to live scenarios. We applied the methodology to a complex live scenario at a major German railway station. The most important aspects and characteristics that are taken into account and should be adjusted are: the topology of a scenario, the positions of sources and targets and the statistical distribution of trajectories between sources and targets, the current schedule of pedestrian appearances and disappearances, the current distribution of free-flow velocities and the density-flow relationship. Some of the parameters are direct input parameters, others, like the density-flow relationship, must be used as target functions for parameter adjustments.

The analysis of the data from our live scenario revealed significant differences to known literature data [1], which underlines the importance of scenario specific measurements as input data and calibration to measured relationships, especially if predictive simulations are attempted. The success of the proposed approach has been tested by comparing the density evolution of the simulated data to the measured data in an area of observation. The simulation predicts the density evolution rather well at least qualitatively and also, to some extent, quantitiatively.

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