Gathering of Data under Laboratory Conditions for the Deep Analysis of Pedestrian Dynamics in Crowds

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Abstract

For the understanding of the dynamics inside crowds reliable empirical data are needed. On that basis the safety and comfort for pedestrians can be increased and models reflecting the real dynamics can be designed.

For that purpose we are developing the free framework PeTrack collecting data from laboratory experiments. With the new integration of the detection of individual codes the presented framework is able to personalize every single trajectory by static information of each participant. The inclusion of inertial sensors allows the tracking of invisible people and capturing the locomotion of the whole body also in dense crowds. Fused information enables the analysis of possible correlations of all observables and thus finding the main influencing parameters for different situations.

1. Introduction

For increasing the safety and comfort for pedestrians, *e.g.* by optimizing the design of escape routes and improving the transport infrastructure at stadiums or stations *etc*., the dynamics of crowds has to be understood. Collecting data like the trajectories of every person with a high temporal and spatial resolution inside a crowd allows a detailed analysis of the movement, provides a basis for quantifications in legal regulations, guidelines and manuals for the construction of pedestrian facilities and enables the design, calibration and verification of microscopic models [49]. Only simulations allow the consideration of each individual, *e.g.* for calculating the evacuation process for large buildings and large scale events.

Some of the contradictions of data and models in the literature can be traced back to insufficient methods of data capturing or inadequate resolution of the measurement in time and space [41]. But microscopic analysis and modelling needs reliable data with a high temporal and spatial resolution [11]. Laboratory experiments investigating pedestrian streams give us the opportunity to selectively analyze parameters independently of undesired influences and adjust them to high densities seldom seen in field studies [21, 44]. Optimal conditions in artificial environments ensure the extraction of high precise data with low error [6]. This makes it reasonable to develop measurement methods providing high resolution in time and space of quantities like density, flow and velocity in combination with small scatter [43, 48]. Trajectories of very high quality [4] enriched with additional data allow the analysis of parameters with only little influence like body height, age or gender *e.g.* on stepping locomotion or interpersonal space.

The level of detail of the extracted information presented in the literature varies. For getting an impression of the overall movement of a crowd, determining abnormal behavior or separating the crowd in areas of different activity the optical flow can help [24, 1, 34]. Also the calculation of the velocity in a certain area is possible without detecting single pedestrians. An estimation of the density is feasible as well [38, 32]. A high level of detail detects and tracks the skeleton of a person. First studies analyzing precise motion sequences already started with the chronophotography in the 19th century [33]. Today the Microsoft Kinect for gaming or motion capturing systems in film productions for steering virtual characters are able to do the skeletal detection and tracking automatically in real-time [17].

For the analysis of peoples' motion the highest possible level would be the best, but for crowds with high density at present no system is able to track the full locomotor system and further personal data. And thus up to now most of the models simulating pedestrian dynamics do not consider the motion of all parts of a body, although taking, for example, the gait into account may enhance the quality of the simulation results [11, 42, 54]. Therefore most experimental data provided for analysis and model pedestrian dynamics are trajectories of every single pedestrian [22, 12, 29, 52, 39, 55, 46, 26, 28, 45, 53], sometimes enriched with some additional global (*e.g.* distribution of age and gender) or individual (*e.g.* body size, head or shoulder

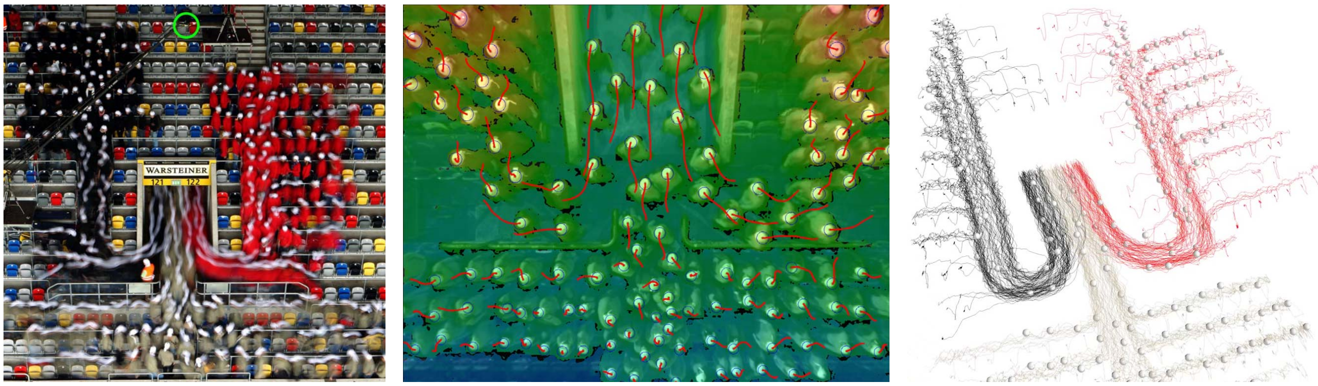

Figure 1. Left: Experiment with 300 pedestrians leaving a grandstand in a stadium through one port. The green circle points to the position of a stereo camera. Center: Plane view of the stereo recording in front of the port color coded to the distance to the camera. The red paths show the head movement in the last second. Right: All trajectories color coded to the shirt color on the left. White spheres indicate the peoples' position to a fixed time.

orientation) information [25].

In this paper new functionalities of our framework PeTrack [5] for gathering data of pedestrians in crowds under laboratory conditions is presented. The development over the last ten years was oriented towards to the needs of miscellaneous requirements [6]. Our free software has been used by various research groups, *e.g.* [19, 18, 16, 35, 53, 40, 13, 30].

2. Data gathering

Performing experiments under laboratory conditions gives the opportunity to analyze parameters of interest under well defined constant conditions. The variability allows a survey of a parameter range e.g. for the bottleneck width or length, or the density inside a corridor. Parameters can be set to values seldom seen in field studies (e.g. very high densities). For self-initiated experiments the location and the structure of the test persons (e.g. culture, fitness, age, gender, size) can be determined. The best modality across the board for detection and tracking of people is vision (i.e. cameras and other imagers) and computer vision is far ahead from other instrumented modalities especially with respect to spatial-resolution and precision metrics [51]. The participants can be marked to ease the detection. For high densities hats are most suitable for this purpose. The cameras can be chosen appropriate to the coverage area and ceiling height. To overlook large spaces a synchronized, calibrated and overlapping camera grid can be used with later concatenation of all trajectory sets. We scaled up to 30 industrial cameras for our largest experiment with up to 1000 participants. Overhead recordings perpendicular to the floor allow a view without occlusion for a range of body heights (see Section 2.2 for handling the occlusion resulting from a large height difference of the participants), so that a microscopic detection and tracking without estimation of the persons' route can be performed. To get constant lighting conditions experiments of us have primarily been made indoor with uniform artificial light.

Our work on the framework PeTrack for the extraction of high accurate trajectories of pedestrians in crowds started 2006 with two synchronized industrial cameras and structured marker on the head of each participant [8]. Structures on a hat give the most accurate results [4]. Multiple structures on a hat can additionally code the head orientation [13]. To minimize the error caused by the perspective view the height of each person was coded by color marker elements [8] or calculated by 3D systems like stereo cameras. 3D systems allow the extraction of paths for uneven terrains like stairs as well [9] (Figure 1 shows an example of the extraction of 3D trajectories from people leaving a grandstand in a stadium). For field observations also an extraction technique without marker based on the disparity map of a stereo camera was integrated into our framework [7]. The software is free [5] and the extracted data from our own experiments are available through an open access database [14].

2.1. Individual code

With the new integration of the detection of individual codes the presented framework is able to personalize every single trajectory by static information of each participant of an experiment. Wearing a hat with the personal code during a series of experiments allows the identification of individuals across different runs. The static information like human factors, age or gender *etc.* can be gathered by handing out questionnaires to the participants.

The detection of individual trajectories by code markers was done by [50, 10] and by us for the first time in the project BaSiGo [31]. For those experiments a Reed-Solomon code was used which is a rotation invariant cyclic marker guaranteeing a minimal Hamming distance of all used codes including error correction (see top left of Figure 2). For recording a large observation space, reducing the probability of occlusion at high densities and to allow a large focal length improving the reading of the code a grid of 24 cameras was mounted above the experiment area.

The detection process of the used Reed-Solomon code was time-consuming. To increase the processing speed a new marker, developed by the research group "Applications of Artificial Vision" of the University of Cordoba, has been integrated into our framework. With the library "a minimal library for Augmented Reality applications based on OpenCV" [15] it is possible to create and detect custom code markers. These binary square fiducial markers are called ArUco markers which have a solid border around the internal code (bottom right of Figure 2 is showing an example).

This condition allows to search for solid borders by a threshold in the whole image. For the resulting candidates the found rectangles are analyzed afterwards. If the content includes a readable bit code it is referred to the corresponding ID. It is possible to correct partly damaged or hidden bit codes. The detection process for the ArUco code marker is approximately 100 times faster than searching for the Reed-Solomon code marker and enables a real time processing for usual frame rates.

The ArUco marker consist of dictionaries differing in the number of bits and the error correction rate which helps to decode partly damaged markers. To configure the detection of the marker parameters such as the threshold to differ between marker border and background, the minimum and maximum pixel size of a marker in the image, the minimum distance between two markers or how to handle a perspective distortion can be adjusted.

To find the code marker candidates and readout the bit code an appropriate sharp image is needed. Therefor motion blur has to be avoided. For normal walking a shutter speed of a maximum of 1/300 s works well. To detect markers which move faster the shutter speed has to be decreased. Furthermore it must be ensured that the color difference between the border of the marker and the surrounding background is sufficient. In addition the resolution of the image and the distance between the markers and the camera should be considered as well so that an adequate number of pixels is covered by a marker. For our tests 27×27 pixels for a 6×6 bit marker like in Figure 2 was sufficient. Decreasing the resolution will result in increasing false detections. The tracking between successive frames permits missing decoding to a certain extent. A slightly slanted view to the border caused by the perspective view and differing head posture is handled by the library of the ArUco markers.

2.2. Inertial measurement unit

Inertial Measurement Units (IMUs) are a combination of sensors which allow to track the movement of an object.

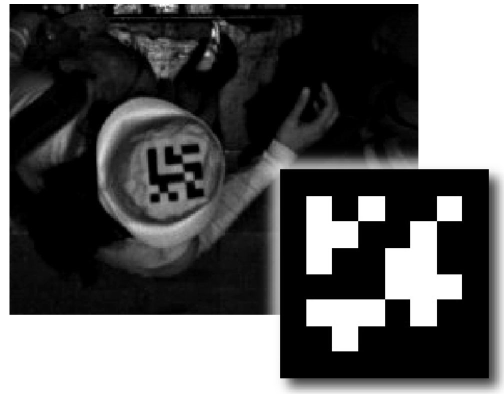

Figure 2. Top left: person wearing a hat with a Reed-Solomon code marker used in the experiments of the project BaSiGo. Bottom right: example of the ARUCO code marker consisting of a solid border for easier detection and an inner 6×6 bit code.

The use of IMUs for experiments studying pedestrian dynamics makes it possible to gain trajectories and information about body movements which can not be extracted by a system needing a free line of sight to the tracked object like a camera system.

IMUs are available as wearable devices and can be attached to a persons body without restricting their movement. They are cheap, light weighted and consist of only few moving parts which make them durable [57, 20]. The use of IMUs keeps the extension of a camera tracking system simple. They are self-contained so that no time is required for the preparation of the tracking area. For our purpose we selected sensors controllable via a wireless network (*e.g.* start and stop logging) and for which the measurements are stored locally on each IMU.

These IMUs consist of an accelerometer, gyroscope and magnetometer measuring the acceleration, angular rate and magnetic field of a moving object. With those readings it is possible to keep track of relative changes of the pedestrians' position. Starting with an initial position the next absolute position is calculated by applying algorithms from the fields of Inertial Navigation or Step-and-Heading Systems:

- Inertial Navigation Systems (INSs): The orientation of the IMU is calculated with the data of the gyroscope or with magnetic field and acceleration data additionally. Afterwards the acceleration can be transformed from the local frame of reference (IMU coordinate system) into the global frame of reference (world coordinate system). In consideration of gravity the current position can be estimated by double integrating the acceleration. [56]

- Step-and-Heading Systems (SHSs): The algorithms consist of three basic parts – step detection, step length estimation and step heading estimation. Steps are detected by the signal of the accelerometer. The heading is calculated from the vertical gyroscope. Then the position is propagated using a fixed or variable stride length in heading direction. [27]

Both systems use body-mounted IMUs. While the sensors for a SHS can be mounted to different positions, most INSs require the IMU to be foot-mounted for a regular phase without acceleration. There are also forms of SHS-INS algorithms mixing both approaches.

For experiments with dense crowds small people, people using a wheelchair or children can be covered by surrounding people and thus invisible for optical systems with a perspective or slanted view. Due to these temporary occlusions the trajectories extracted with a camera system are incomplete. To fill those gaps the respective persons can be equipped with IMUs whose signals are used for the reconstruction of their trajectories. By attaching multiple sensors to a persons' body tracking of the full body motion as in [2, 37, 36] is possible which allows a deeper understanding of interactions in crowds.

If the sensor is placed at the upper body of a walking person it is possible to calculate the vertical fluctuation of the persons' height. During the walking process the height of the person reaches its minimum when both feet touch the ground. The signals of the IMU can be used to reconstruct the up and down movement. The actual height is crucial for the calculation of the distance to the camera and the depending global position of the head [8]. In prior experiments stereo cameras were used for this purpose which are susceptible to optical distortions of the images [9].

Tracking algorithms for IMUs have to deal with a rapid accumulation of error. The sensors' biases and noises lead to an imprecise acceleration and heading information and thus to a large drift of the position, if calculated without an error correction. The error can be restricted by applying filter for IMU data fusing. Additionally, for occluded people it is known that their position must be near the center of the polygon formed by the heads of neighboring people and can only be located in occluded areas. Besides, characteristics of the enclosing group can be assumed for the covered person as well such as main direction of motion and velocity. Furthermore constraints are given by the geometry setup (walls, obstacles) and the laboratory conditions simplify the tracking. The participants will follow specific instructions which makes a very rough estimation of the trajectories possible (*e.g.* the movement to an exit).

2.3. Correlation of observables

Data from different sensors *e.g.* to detect the person or the persons' height, to read out a code of a structured marker or to measure the acceleration of body parts have to be fused. The calibration in space has to be done and the synchronization in time can be made by absolute time stamps, a special audio signal or light flashing depending on the sensor performance. Beside the accuracy of the single sensor data the merging of the data has to be correct to be able to derive correlations between the measured quantities.

For some studies the extracted data can be used directly like the path of the peoples' head for analyzing the stepping locomotion. For other derived quantities these data have to be filtered. To determine *e.g.* the velocity in the main moving direction the swaying inside the trajectory has to be smoothed best done by considering the stepping locomotion or the locomotion of the whole body.

3. Conclusions and Outlook

The dynamics of a crowd and the behavior of a person have a large number of influencing parameters. To analyze and thus to understand the interdependencies comprehensive and reliable data of all persons and the surrounding like the geometry of the facility or the lighting conditions are needed so that main influencing parameters in a special situation can be determined.

With the integration of individual codes the presented framework is able to personalize every single trajectory by static information of each participant. The inertial sensors allow the tracking of invisible people and capturing the locomotion of the whole body also in dense crowds. Fused information enables the analysis of possible correlations of all observables.

The captured dynamic sensor data focus up to now on the physical momentum inside the crowd. For a better exploration of the social and psychological character of the crowd and to combine aspects of behavioral biology [3] and social psychology [47] with the natural scientist perspective as a first step sensors measuring the electrodermal activity will be utilized in the next upcoming project. For other requested projects also eye tracker are planned to be used to capture the objects or signs getting most attention.

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References

[1] S. Ali and M. Shah. A lagrangian particle dynamics approach for crowd flow segmentation and stability analysis. In *Conference on Computer Vision and Pattern Recognition*, pages 1–6, ,Minneapolis, Minnesota, USA, Jun 2007. IEEE Computer Society. 1

[2] F. Attal, S. Mohammed, M. Dedabrishvili, F. Chamroukhi, L. Oukhellou, and Y. Amirat. Physical human activity recognition using wearable sensors. *Sensors*, 15(12):31314–31338, 2015. 4

[3] N. W. F. Bode, S. Holl, W. Mehner, and A. Seyfried. Disentangling the impact of social groups on response times and movement dynamics in evacuation. *PLOS ONE*, 10(3):0121227, Mar 2015. 4

[4] M. Boltes, S. Holl, A. Tordeux, A. Seyfried, A. Schadschneider, and U. Lang. Influences of extraction techniques on the quality of measured quantities of pedestrian characteristics. In *Proceedings of Pedestrian and Evacuation Dynamics 2016*, pages 500–547, 2016. 1, 2

[5] M. Boltes and D. Salden. Software `petrack`. `http://ped.fz-juelich.de/petrack` (30.04.2017). 2

[6] M. Boltes and A. Seyfried. Collecting Pedestrian Trajectories. *Neurocomputing, Special Issue on Behaviours in Video*, 100:127–133, 2013. 1, 2

[7] M. Boltes and A. Seyfried. Tracking People in Crowded Scenes. In U. Weidmann, U. Kirsch, and M. Schreckenberg, editors, *Pedestrian and Evacuation Dynamics 2012*, pages 533–542. Springer Berlin Heidelberg, 2014. 2

[8] M. Boltes, A. Seyfried, B. Steffen, and A. Schadschneider. Automatic Extraction of Pedestrian Trajectories from Video Recordings. In Klingsch et al. [23], pages 43–54. 2, 4

[9] M. Boltes, A. Seyfried, B. Steffen, and A. Schadschneider. Using Stereo Recordings to Extract Pedestrian Trajectories Automatically in Space. In R. D. Peacock, E. D. Kuligowski, and J. D. Averill, editors, *Pedestrian and Evacuation Dynamics 2010*, pages 751–754. Springer Berlin Heidelberg, 2011. 2, 4

[10] M. Bukáček, P. Hrabák, and M. Krbálek. Experimental study of phase transition in pedestrian flow. *Transportation Research Procedia*, 2(0):105–113, 2014. 2

[11] M. Chraibi, A. Seyfried, and A. Schadschneider. Generalized centrifugal force model for pedestrian dynamics. *Physical Review E*, 82:046111, 2010. 1

[12] W. Daamen and S. Hoogendoorn. Capacity of doors during evacuation conditions. *Procedia Engineering, 1st Conference on Evacuation Modeling and Management*, 3(0):53–66, 2010. 1

[13] T. Ezaki, K. Ohtsuka, M. Chraibi, M. Boltes, D. Yanagisawa, A. Seyfried, A. Schadschneider, and K. Nishinari. Inflow process of pedestrians to a confined space. *Collective Dynamics*, 1:1–18, 2016. 2

[14] Forschungszentrum Jülich, Jülich Supercomputing Centre. Database of experiments. `http://ped.fz-juelich.de/database` (30.04.2017). 2

[15] S. Garrido-Jurado, R. Muoz-Salinas, F. Madrid-Cuevas, and M. Marn-Jimnez. Automatic generation and detection of highly reliable fiducial markers under occlusion. *Pattern Recognition*, 47(6):2280 – 2292, 2014. 3

[16] M. K. Gdoura, R. Löhner, E. Haug, and B. Gawenat. On the influence of columns in densely populated corridors. In *Pedestrian and Evacuation Dynamics 2014*, 2014. 2

[17] A. Gmiterko and T. Liptak. Motion capture of human for interaction with service robot. *American Journal of Mechanical Engineering*, 1(7):212–216, 2013. 1

[18] M. Haghani and M. Sarvi. Stated and revealed exit choices of pedestrian crowd evacuees. *Transportation Research Part B: Methodological*, 95:238 – 259, 2017. 2

[19] M. Haghani, M. Sarvi, Z. Shahhoseini, and M. Boltes. How simple hypothetical-choice experiments can be utilized to learn humans' navigational escape decisions in emergencies. *PLOS ONE*, 11(11):1–24, Nov 2016. 2

[20] F. Hoflinger, R. Zhang, and L. M. Reindl. Indoor-localization system using a micro-inertial measurement unit (imu). In *European Frequency and Time Forum (EFTF), 2012*, pages 443–447, Apr 2012. 3

[21] S. Holl and A. Seyfried. Laboratory experiments on crowd dynamics. *inSiDE (Innovatives Supercomputing in Deutschland)*, 11(2), 2013. 1

[22] S. Hoogendoorn, W. Daamen, and P. Bovy. Extracting microscopic pedestrian characteristics from video data. In *TRB2003 Annual Meeting*, 2003. 1

[23] W. W. F. Klingsch, C. Rogsch, A. Schadschneider, and M. Schreckenberg, editors. *Pedestrian and Evacuation Dynamics 2008*. Springer Berlin Heidelberg, Jan 2010. 5, 6

[24] B. Krausz and C. Bauckhage. Loveparade 2010: Automatic video analysis of a crowd disaster. *Computer Vision and Image Understanding, Special issue on Semantic Understanding of Human Behaviors in Image Sequences*, 116(3):307–319, 2012. 1

[25] S. Lemercier, M. Moreau, M. Moussaïd, G. Theraulaz, S. Donikian, and J. Pettré. Reconstructing motion capture data for human crowd study. In J. Allbeck and P. Faloutsos, editors, *Motion in Games*, volume 7060 of *Lecture Notes in Computer Science*, pages 365–376. Springer Berlin Heidelberg, 2011. 2

[26] L. Lian, X. Mai, W. Song, and Y. K. Kit. An experimental study on four-directional intersecting pedestrian flows. *J. Stat. Mech*, page P08024, 2015. 1

[27] T. Lin, L. Li, and G. Lachapelle. Multiple sensors integration for pedestrian indoor navigation. In *Indoor Positioning and Indoor Navigation (IPIN), 2015 International Conference on*, pages 1–9, Oct 2015. 4

[28] X. Liu, W. Song, L. Fu, and Z. Fang. Experimental study of pedestrian inflow in a room with a separate entrance and exit. *Physica A: Statistical Mechanics and its Applications*, 442:224–238, 2016. 1

[29] X. Liu, W. Song, and J. Zhang. Extraction and quantitative analysis of microscopic evacuation characteristics based on digital image processing. *Physica A: Statistical Mechanics and its Applications*, 388(13):2717–2726, Jul 2009. 1

[30] Y. Liu, X. Shi, Z. Ye, N. Shiwakoti, and J. Lin. Controlled experiments to examine different exit designs on crowd evacuation dynamics. In *16th COTA International Conference of Transportation Professionals*, pages 779–790, 2016. 2

[31] W. Mehner, M. Boltes, and A. Seyfried. Methodology for generating individualized trajectories from experiments. In V. L. Knoop and W. Daamen, editors, *Traffic and Granular Flow 2015*, pages 3–10, 2015. 2

[32] P. Morerio, L. Marcenaro, and C. S. Regazzoni. People count estimation in small crowds. In *Advanced video and signal-based surveillance (AVSS), 2012 IEEE Ninth International Conference on*, pages 476–480, 2012. 1

[33] E. Muybridge. *Animal locomotion, Plate 519*. Da Capo Press New York, 1887. 1

[34] S. S. Pathan and K. Richter. Pedestrian behavior analysis with image-based method in crowds. In *Traffic and Granular Flow 2013*, pages 187–194. Forschungszentrum Jülich, Springer, 2015. 1

[35] L. Petersen. Pedestrian experiment to verify a hopf bifurcation in pedestrian flow. *DTU newspaper*, 2012. 2

[36] G. Pons-Moll, A. Baak, T. Helten, M. Müller, H.-P. Seidel, and B. Rosenhahn. Multisensor-fusion for 3d full-body human motion capture. In *CVPR*, pages 663–670, 2010. 4

[37] D. Roetenberg, H. Luinge, and P. Slycke. Xsens mvn: full 6dof human motion tracking using miniature inertial sensors. *Xsens Motion Technologies BV, Tech. Rep*, 2009. 4

[38] D. Ryan, S. Denman, S. Sridharan, and C. Fookes. An evaluation of crowd counting methods, features and regression models. *Computer Vision and Image Understanding*, 130:1–17, 2014. 1

[39] S. Saadat and K. Teknomo. Automation of pedestrian tracking in a crowded situation. In R. D. Peacock, E. D. Kuligowski, and J. D. Averill, editors, *Pedestrian and Evacuation Dynamics*, pages 231–239. Springer US, 2011. 1

[40] I. Sakellariou, O. Kurdi, M. Gheorghe, D. Romano, P. Kefalas, F. Ipate, and I. Niculescu. Crowd formal modelling and simulation: The sa'yee ritual. In *Computational Intelligence (UKCI), 2014 14th UK Workshop on*, pages 1–8, Sep 2014. 2

[41] A. Schadschneider, W. Klingsch, H. Kluepfel, T. Kretz, C. Rogsch, and A. Seyfried. *Encyclopedia of Complexity and System Science*, volume 5, chapter Evacuation Dynamics: Empirical Results, Modeling and Applications, pages 3142–3176. Springer Berlin Heidelberg, 2009. 1

[42] M. J. Seitz and G. Köster. Natural discretization of pedestrian movement in continuous space. *Phys. Rev. E*, 86:046108, Oct 2012. 1

[43] A. Seyfried, M. Boltes, J. Kähler, W. Klingsch, A. Portz, T. Rupprecht, A. Schadschneider, B. Steffen, and A. Winkens. Enhanced empirical data for the fundamental diagram and the flow through bottlenecks. In Klingsch et al. [23], pages 145–156. 1

[44] X. Shi, Z. Ye, N. Shiwakoti, and Z. Li. A review of experimental studies on complex pedestrian movement behaviors. In *CICTP 2015*, pages 1081–1096, 2015. 1

[45] N. Shiwakoti, Y. Gong, X. Shi, and Z. Ye. Examining influence of merging architectural features on pedestrian crowd movement. *Safety Science*, 75:15–22, 2015. 1

[46] N. Shiwakoti, X. Shi, Y. Zhirui, and W. Wang. Empirical study on pedestrian crowd behaviour in right angled junction. In *37th Australasian Transport Research Forum (ATRF)*, 2015. 1

[47] A. Sieben, J. Schumann, and A. Seyfried. Collective phenomena in crowds - where pedestrian dynamics need social psychology. *PloS one*, under review. 4

[48] B. Steffen and A. Seyfried. Methods for measuring pedestrian density, flow, speed and direction with minimal scatter. *Physica A*, 389(9):1902–1910, May 2010. 1

[49] B. Steffen, A. Seyfried, and M. Boltes. Reliability issues in the microscopic modeling of pedestrian movement. In H. K. Pavel Exner, editor, *Mathematical results in Quantum Physics*, pages 254–259, Czech Republic, Sep 2011. 1

[50] D. Stuart, K. M. Christensen, A. Chen, Y. Kim, and Y. Chen. Utilizing augmented reality technology for crowd pedestrian analysis involving individuals with disabilities. In *Proceedings of the ASME International Design Engineering Technical Conferences & Computers and Information in Engineering Conference*, Portland, Oregon, 2013. 2

[51] T. Teixeira, G. Dublon, and A. Savvides. A survey of human-sensing: Methods for detecting presence, count, location, track, and identity. *ACM Computing Surveys*, 5(1), 2010. 2

[52] W. Tian, W. Song, J. Ma, Z. Fang, A. Seyfried, and J. Liddle. Experimental study of pedestrian behaviors in a corridor based on digital image processing. *Fire Safety Journal*, 47(0):8–15, 2012. 1

[53] A. Tomoeda, D. Yanagisawa, and K. Nishinari. Escape velocity of the leader in a queue of pedestrians. In *Traffic and Granular Flow 2013*, pages 213–218. Forschungszentrum Jülich, Springer, 2015. 1, 2

[54] I. von Sivers and G. Köster. Dynamic stride length adaptation according to utility and personal space. *Transportation Research Part B: Methodological*, 74:104 – 117, 2015. 1

[55] S. C. Wong, W. L. Leung, S. H. Chan, W. H. K. Lam, N. H. C. Yung, C. Y. Liu, and P. Zhang. Bidirectional Pedestrian Stream Model with Oblique Intersecting Angle. *Journal of Transportation Engineering*, 136(3):234–242, 2010. 1

[56] O. J. Woodman. An introduction to inertial navigation. *University of Cambridge, Computer Laboratory, Tech. Rep. UCAMCL-TR-696*, 14:15, 2007. 3

[57] O. J. Woodman. *Pedestrian localisation for indoor environments*. dissertation, University of Cambridge, 2010. 3