

Hybrid Tracking System for Pedestrians in Dense Crowds

Jette Schumann, Maik Boltes and Armin Seyfried

Abstract For a proper understanding and modeling of pedestrian dynamics reliable empirical data are needed. Often the level of heterogeneity of pedestrians in laboratory experiments does not correspond with the level in the field. New studies have been carried out to examine one factor of heterogeneity by considering people with physical, mental and age-related disabilities. In these studies a novel hybrid tracking system consisting of a camera system and Inertial Measurement Units (IMUs) was used for the first time. The use of IMUs solves the critical issue of occlusion caused by the perspective view of the camera system and different body heights expected for participating wheelchair users in dense crowds. The IMUs act as an extension of the camera system to enable a complete data extraction of the participants' trajectories and gathering of additional movement data. This paper focuses on the hybrid tracking system and proposes a tracking procedure for wheelchair users participating in these studies.

1 Introduction

The understanding of the nature of pedestrian streams is a fundamental step towards a safe and comfortable design of public buildings and facilities. To get new insights laboratory pedestrian experiments are conducted with varying factors influencing the movement of the pedestrians such as the width of a bottleneck or the motivation of the participants. For analyzing the movement in detail a complex tracking system is needed which provides data of each participant with a high temporal and spatial resolution [3]. Based on the extracted information important measures for transport characteristics such as flow, velocity and density can be determined describing e. g. the level of comfort or safety.

Jette Schumann, Maik Boltes and Armin Seyfried
Institute for Advanced Simulation, Forschungszentrum Jülich, Jülich, Germany e-mail:
{j.schumann;m.boltes;a.seyfried}@fz-juelich.de

In our past experiments [8, 9, 5] the heterogeneous composition of pedestrian streams was not considered, even though interactions between the different groups of people might affect the dynamics of the whole crowd. To gather data for a deeper analysis of the influence of the heterogeneity of a crowd on its movement new experiments have been carried out involving people with and without disabilities. Those experiments have been conducted within the scope of the research project SiME [2] with the aim of improving the safety for people with physical, mental and age-related disabilities.

Consisting of several cameras on the ceiling, the basic tracking system is not capable of detecting small people, especially wheelchair users, in a crowd. Because of the perspective view small people might not be visible to the cameras when they are surrounded by taller people temporarily. For a comprehensive analysis of pedestrian streams incomplete trajectories should be prevented. To tackle this problem an extended tracking system is needed. Usually the pedestrian experiments are performed indoor for stable and homogeneous light conditions and therefore the tracking system must be applicable in buildings as well.

Due to the arising needs of location-based services in areas like medical technology, advertising, tourism, sports or rescue many indoor localization technologies have been developed over the past years and can be classified into [16]:

- Wireless-communication-based localization technologies such as WiFi, Bluetooth, ultra-wideband, ultrasound, radio frequency, etc.,
- Dead reckoning techniques using motion sensors and odometers and
- Video scene analysis using methods for tag detection, scene matching or tracking moving objects (which is partly implemented by the camera tracking system).

A major advantage of dead reckoning techniques is that no additional infrastructure is needed in contrast to other systems. For Pedestrian Dead Reckoning (PDR) Inertial Measurement Units (IMUs) are widely used. Wearable IMUs are available as Micro-Electro-Mechanical Systems (MEMS), which can be attached to the persons' body without restricting their movement. They are cost-efficient, lightweighted and consist of only few moving parts which makes them durable [7, 18]. IMUs are self-contained so that no time is required for the preparation of the tracking area. The use of IMUs keeps the extension of the camera system simple, but requires methods for calibration, fusion and restriction of the drift (see Sect. 2). Besides it is possible to track movement processes inside the crowd which are not perceptible by cameras such as the bobbing movement of steps and even full body tracking [1, 14, 13].

The focus of this paper is the tracking of wheelchair users with IMUs. Due to noisy IMU signals it is necessary to constrain the movement of the wheelchair users with data from the camera system resulting in a hybrid tracking algorithm fusing IMU and camera data.

2 Hybrid Tracking System

For the SiME studies the movement of the test persons has been recorded with a camera detection system (see Fig. 1). The cameras were aligned in a grid on the ceiling so that the complete coverage of the area was ensured. For a more precise detection the participants were wearing markers in form of caps which color encodes their height. In addition IMUs were worn by wheelchair users that might get covered due to their small height. To distinguish the wheelchair users (and the IMUs they have worn) labels were attached to their shoulders. The IMUs have a size of just a few centimeters and were attached with clamps or tape to the wheelchairs. As the camera tracking system is described in [4] this section focuses on the IMU tracking algorithms and the fusion of camera and IMU data.



Fig. 1 Perpendicular view of the central camera for studies with wheelchair users in two different geometries is shown. Participants are wearing colored caps for automatic trajectory extraction.

2.1 IMU Tracking

The used IMUs from Sabellabs [11] consist of an accelerometer, a gyroscope and a magnetometer which provide measurements along three axis respectively. With those inertial sensors it is possible to keep track of movement changes by measuring the acceleration, rotation rate and magnetic field. For the tracking of the homogeneous movement of a wheelchair algorithms of Inertial Navigation Systems (INS) [17] can be applied which are also used for tracking mobile robots as in [6, 10]. Starting from an initial position the next absolute position is calculated using the measured sensor signals. The basic approach of an INS algorithm can be described as follows:

1. The current orientation of the device is calculated based on several sensor data. For this purpose the orientation filter of Madgwick [12] is used as described in [15]. The filter provides an orientation represented as a quaternion by a fusion of accelerometer, gyroscope and magnetometer data.

2. This is followed by a rotation of the acceleration data from the local frame of reference (IMU coordinate system) to the global frame of reference (world coordinate system where the z-axis points down) by a multiplication with the calculated quaternion.
3. By subtracting the earth gravity from the z-axis and double integrating the global acceleration the position can be calculated.

Those steps are repeated for each time step which comes along with an accumulation of errors and therefore a drift in position. Methods for constraining the drift are needed (see Subsect. 2.2.2).

2.2 *Fusion of Camera and IMU Data*

For the tracking of pedestrians with two different tracking systems the datasets need to be synchronized and aligned at first. After that it is possible to improve the IMU tracking quality by fusing the IMU data with input of the camera system.

2.2.1 Merging the Datasets

To receive a consistent dataset of camera and IMU data a synchronization in time is needed. With a dedicated IMU hub device it is possible to send a signal to each IMU so that they are synchronized among each other and to emit a LED signal which is visible by the camera system. By pairing the corresponding frame in the camera data and the record in the IMU data the datasets are synchronized.

When extracting trajectories from the camera data a coordinate system needs to be chosen which is often aligned to the geometry setup. The global IMU coordinate system needs to be aligned with this camera coordinate system. For this purpose the initial velocity vector of the wheelchair (calculated from IMU data) is aligned with the velocity vector of the wheelchair calculated from the camera data (see [15]).

2.2.2 Constraining the Drift

As described in [18] the tracking of a person with general purpose inertial navigation algorithms is not possible because of the rapid accumulation of error. To limit the drift of the wheelchair trajectory additional data of the surrounding people extracted by the camera system can be used. In case of an occlusion characteristics of the enclosing group are applicable for the occluded person as well.

Based on this idea the velocity of the wheelchair user is corrected by the velocity of the pushing person as a first approach. It is assumed that the velocity of the wheelchair user, v_{imu} , calculated from IMU data (at step i) is close to the velocity of the pushing person, v_{pusher} , calculated from the trajectory extracted with the camera

system. If the difference v_{diff} defined as in (1) exceeds a predefined range v_{range} as in (2) at step k the noisy velocity of the wheelchair v_{imu} is corrected by adapting the global acceleration acc_{global} for the previous (since last correction) and future time period. The basic idea for the adaption is to estimate the difference in acceleration acc_{diff} that caused the difference in velocity v_{diff} as in (3) with Δt defining the time since the last correction from step k_{prior} to k . The global acceleration is corrected by adding acc_{diff} as in (4) for previous time steps starting after the last adaption k_{prior} . After each adaption v_{imu} is calculated again based on the corrected global acceleration. Following adaption takes place at the earliest at $i > k$.

Due to the homogeneous movement of the wheelchair without up and down movements (and since only two-dimensional trajectories are extracted with the camera system) the velocity along the z-axis is neglected and set to zero. An example dataset for one adaption step is shown in Fig. 2.

$$v_{diff,i} = |v_{imu,i} - v_{pusher,i}| \quad \forall i \in \{1, \dots, n\} \quad (1)$$

$$v_{diff,k} > v_{range} \quad (2)$$

$$acc_{diff,k} = v_{diff,k} / \Delta t \quad (3)$$

$$acc_{global,j} = acc_{global,j} + acc_{diff,k} \quad \forall j \in \{k_{prior} + 1, \dots, n\} \quad (4)$$

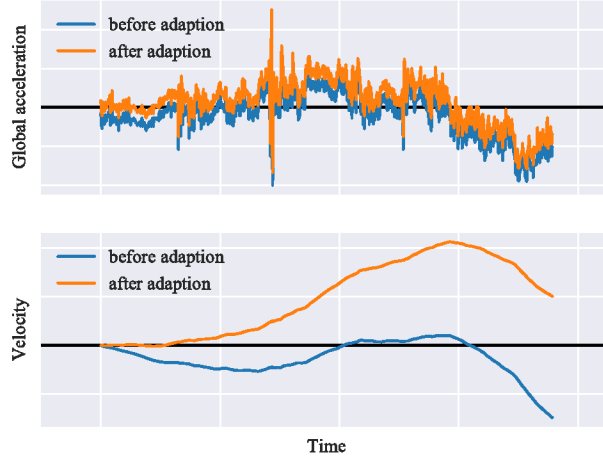


Fig. 2 Qualitative example for retroactive adaption of the acceleration and velocity: The black line represents the zero axis. It is assumed that a noisy acceleration (blue, upper figure) leads to an wrong velocity at the end (blue, lower figure). To reach a given velocity (given by a reference value) the acceleration is adapted (orange, upper figure). In this way the adapted velocity (orange, lower figure) reaches the reference value. For this example the velocity was underestimated at first and reaches a higher reference value after the adaption.

3 Results

To evaluate the tracking procedure it was tested on a SiME dataset of a wheelchair user who was visible for the whole time so that the ground truth (camera data) is available. The sensor was attached to the backrest of the wheelchair. The analysis of the velocity of the pusher and wheelchair user (based on the positions extracted with the camera data) showed that the absolute maximum difference of their norms does not exceed 0.3 m/s which value was taken as a reference for v_{range} . The highest difference in velocities appears when the direction of the trajectory changes significantly because the direction (and velocity) of the wheelchair user changes not at the same moment but some milliseconds before.

The lower v_{range} the more information of the pushing person is used for calculating the IMU trajectory. A balance between v_{range} and the number of adaptations needs to be found. For analyzing this relation the number of adaptations, the maximum error of the IMU trajectory (compared to the trajectory extracted with the camera system) and the time periods between consecutive adaptations were investigated. In addition the same analysis was done with the velocity of the ground truth as reference value. So instead of v_{pusher} the velocity of the wheelchair extracted with the camera system was used for calculating v_{diff} and the subsequent adaption. On this basis the influence of the referenced velocity (used for adaption) on the tracking quality can be investigated. The results are shown in Tab. 1.

For this example a v_{range} of 0.3 m/s seems to be suitable to adapt the velocity in a proper way with only 9 adaptations in intervals of nearly 1 to 4 seconds. The analysis has shown that a more accurate reference value (ground truth) decreased the maximum error by almost the half. Based on this the calculation of the referenced velocity should be improved in future steps e. g. by taking the velocity of other surrounding people into account.

A selection of resulting trajectories can be seen in Fig. 3, 4 and 5. The figures show the trajectories of the wheelchair user (blue) and the pushing person (orange) extracted with the camera system and the IMU trajectory of the wheelchair (green) moving through a bottleneck. The trajectory of the pusher is fluctuating due to the swaying of the person while walking and the tracking of the head by the camera.

Table 1 Overview of analysis results for a total tracking time of 15 seconds for the adaption with the velocity of the pusher and ground truth as reference value.

v_{range} (m/s)	Reference velocity from	Number of adaptions	Maximum error (m)	Longest period be- tween adaptions (ms)	Shortest period be- tween adaptions (ms)
0.1	pusher	34	0.32	114	15
0.1	ground truth	16	0.29	199	34
0.3	pusher	9	0.49	363	84
0.3	ground truth	8	0.25	252	100
0.5	pusher	5	0.97	310	195
0.5	ground truth	4	0.58	374	227

Fig. 3 Trajectories for $v_{range} = 0.1$ m/s and v_{pusher} as reference value for correction. Due to the low v_{range} the swaying of the pusher is also visible in the IMU trajectory.

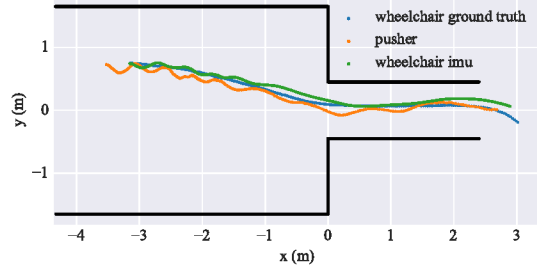


Fig. 4 Trajectories for $v_{range} = 0.3$ m/s and v_{pusher} as reference value for correction. The swaying of the pusher is not visible in the IMU trajectory anymore. Nevertheless it is not as smooth as the ground truth due to the correction with a roughly similar reference velocity.

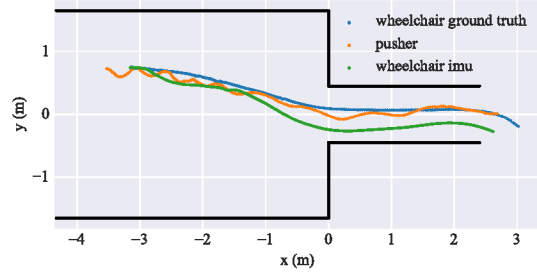
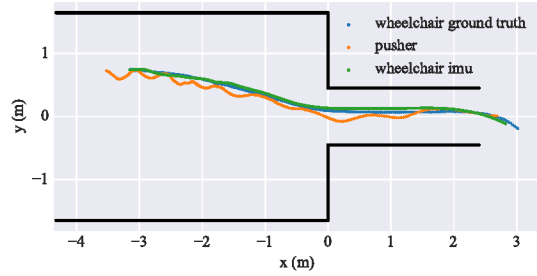


Fig. 5 Trajectories for $v_{range} = 0.3$ m/s and v_{ground_truth} as reference value for correction. By correcting with a more accurate velocity the tracking gets much better.



4 Conclusion and Outlook

A hybrid tracking system consisting of cameras and IMUs was developed and tested for tracking wheelchair users in dense crowds. By including the velocity of the pushing person (extracted with a camera system) it is possible to limit the drift of the wheelchair user (calculated with IMU data) resulting in a trajectory with a maximum error of a half meter over a period of 15 seconds. The fusion of IMU data with a more accurate velocity is promising and would result in a higher tracking quality.

In future work additional restrictions of the IMU trajectory will be implemented. It is possible to limit the drift by taking the velocity and position of surrounding people (not just the pusher) and walls into account. Wheelchairs were actually equipped with several IMUs so that the fusion of IMU data of multiple sensors attached to one wheelchair will be examined. Besides IMU tracking algorithms will be extended by approaches to track walking people (e. g. step detection) and human motion processes (e. g. orientation of shoulders) as well.

Acknowledgements Thanks to the support from the Federal Ministry of Education and Research of Germany (BMBF, FKZ 13N13946) the SiME experiments could have been conducted and the novel hybrid tracking system could be realized.

References

1. Attal, F., Mohammed, S., Dedabrishvili, M., Chamroukhi, F., Oukhellou, L., Amirat, Y.: Physical human activity recognition using wearable sensors. *Sensors* **15**(12), 31,314–31,338 (2015)
2. Boltes, M., Holl, S.: SiME - Improved safety for disabled people. inSiDE **14**(1), 75 (2016)
3. Boltes, M., Schumann, J., Salden, D.: Gathering of data under laboratory conditions for the deep analysis of pedestrian dynamics in crowds. In: 2017 14th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS) (2017). DOI 10.1109/AVSS.2017.8078471
4. Boltes, M., Seyfried, A., Steffen, B., Schadschneider, A.: Automatic Extraction of Pedestrian Trajectories from Video Recordings. In: W.W.F. Klingsch, C. Rogsch, A. Schadschneider, M. Schreckenberg (eds.) *Pedestrian and Evacuation Dynamics 2008*, pp. 43–54. Springer Berlin Heidelberg (2010). DOI 10.1007/978-3-642-04504-2-3
5. Cao, S., Seyfried, A., Zhang, J., Holl, S., Song, W.: Fundamental diagrams for multidirectional pedestrian flows. *Journal of Statistical Mechanics: Theory and Experiment* **2017**(3), 033,404 (2017). URL <http://stacks.iop.org/1742-5468/2017/i=3/a=033404>
6. Cho, B.S., sung Moon, W., Seo, W.J., Baek, K.R.: A dead reckoning localization system for mobile robots using inertial sensors and wheel revolution encoding. *Journal of Mechanical Science and Technology* **25**(11), 2907–2917 (2011). DOI 10.1007/s12206-011-0805-1
7. Hoflinger, F., Zhang, R., Reindl, L.M.: Indoor-localization system using a micro-inertial measurement unit (imu). In: European Frequency and Time Forum (EFTF), 2012, pp. 443–447 (2012). DOI 10.1109/EFTF.2012.6502421
8. Holl, S., Seyfried, A.: Hermes - an Evacuation Assistant for Mass Events. inSiDE **7**(1), 60–61 (2009)
9. Holl, S., Seyfried, A.: Laboratory experiments on crowd dynamics. inSiDE (Innovatives Supercomputing in Deutschland) **11**(2) (2013)
10. Koch, J., Hillenbrand, C., Berns, K.: Inertial navigation for wheeled robots in outdoor terrain. In: Proceedings of the Fifth International Workshop on Robot Motion and Control, 2005. RoMoCo05. Institute of Electrical & Electronics Engineers (IEEE) (2005). DOI 10.1109/romoco.2005.201419
11. Labs, S.: Sabel sense (2017). URL <https://sabellabs.com/sense/>
12. Madgwick, S.O.H., Harrison, A.J.L., Vaidyanathan, R.: Estimation of IMU and MARG orientation using a gradient descent algorithm. In: 2011 IEEE International Conference on Rehabilitation Robotics. Institute of Electrical and Electronics Engineers (IEEE) (2011). DOI 10.1109/icorr.2011.5975346
13. Pons-Moll, G., Baak, A., Helten, T., Müller, M., Seidel, H.P., Rosenhahn, B.: Multisensor-fusion for 3d full-body human motion capture. In: CVPR, pp. 663–670 (2010)
14. Roetenberg, D., Luinge, H., Slycke, P.: Xsens mvn: full 6dof human motion tracking using miniature inertial sensors. Xsens Motion Technologies BV, Tech. Rep (2009)
15. Schumann, J., Boltes, M.: Tracking of wheelchair users in dense crowds. In: 2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN) (2017)
16. Stojanović, D., Stojanović, N.: Indoor localization and tracking: Methods, technologies and research challenges. *Facta Universitatis, Series: Automatic Control and Robotics* **13**(1), 57–72 (2014)
17. Woodman, O.J.: An introduction to inertial navigation. University of Cambridge, Computer Laboratory, Tech. Rep. UCAMCL-TR-696 **14**, 15 (2007)
18. Woodman, O.J.: Pedestrian localisation for indoor environments. dissertation, University of Cambridge (2010)