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The potential of agent-based modelling for verification of people trajectories based on smartphone sensor data

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Abstract. In this paper the potential of smartphone sensor data for verification of people trajectories derived from airborne remote sensing data are investigated and discussed based on simulated test recordings in the city of Osnabrueck, Germany. For this purpose, the airborne imagery is simulated by images taken from a high building with a typical single lens reflex camera. The smartphone data required for the analysis of the potential is simultaneously recorded by test persons on the ground. In a second step, the quality of the smartphone sensor data is evaluated regarding the integration into simulation and modelling approaches. In this context we studied the potential of the agent-based modelling technique concerning the verification of people trajectories.

1. Introduction

Talking about the Digital Earth in recent years, the term “real time” often comes up and is a key feature looking to the future [1]. In the project “VABENE” of the German Aerospace Center (DLR), the real-time aspect regarding airborne remote sensing was accomplished by an on-board computing system combined with a direct data transfer to ground stations via exterior antenna [2]. By combing this real-time remote sensing data with additional data, like in-situ sensor data, it might be possible to eliminate the disadvantages of remote sensors like the dependency on the weather conditions (e.g. cloud coverage) or the inability to provide information for occluded areas (e.g. under bridges or in buildings) for many applications with the need of real-time information like disaster management [3]. Furthermore, traditional image processing algorithms can be adapted to suit real-time remote sensing data and offer additional information for such applications [4]. For this purpose, this paper presents the potential of in-situ sensor data (in this case smartphone data) for the verification of single person trajectories derived via image processing techniques.

The airborne imagery used in this work is simulated in a test recording by images taken from a high building with a typical single lens reflex camera. This simulation makes the recordings easier to repeat on the one hand as well as much cheaper on the other hand than using actual airborne sensed images. Furthermore, the results are reproducible and comparable. The smartphone data required for the analysis of the potential is simultaneously recorded by test persons on the ground.

In a second step, the quality of the recorded smartphone sensor data is evaluated regarding the integration into simulation and modelling approaches like evacuation simulation. In this context we study the potential of the agent-based modelling technique concerning the verification of people trajectories as it offers the possibility to model real-world dynamics, especially flows of humans, cars or any other individual.

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In the following section 2 the related work in the field of agent-based modelling regarding people dynamics is shown to emphasise the potential and the limitations of this modelling technique. Afterwards, section 3 describes the experimental setup for the data recording in the city of Osnabrueck and the resulting datasets. The recorded smartphone sensor data is then analysed in section 4 concerning the potential for the integration into an agent-based model. Eventually, section 5 concludes the results of this paper and delivers an outlook for future work.

2. Related work in agent-based modelling for people dynamics

The history of agent-based modelling starts with cellular automaton by Stanislaw Ulam and John von Neumann in the 1940s [5], which has a limited complexity in its decision rules and a defined rectangular grid that changes its values over time. One of the ABM's pioneers is the social scientist Thomas Schelling who was the first to use ABM in its model of the formation of segregated neighbourhoods [6]. Nowadays, ABM is used in many areas of application, like evacuation management [7], traffic and customer flows [8][9], dynamics of the stock market [10] as well as social simulations [11].

Early approaches, regarding agent-based pedestrian flow modelling, were made in the late 1990s [12][13][14]. The majority of studies stated that the ABM is highly applicable for this purpose although the models reveal some shortcomings. The agent movement behaviour was often unreliable and required fine-tuning to fit realistic walking pattern. Furthermore, the models did not contain much agent interaction like group dynamics or personal relationships. The coupling of ABM with a geographical information system (GIS) to work in a georeferenced environment as well as to link the behaviours and the impacts of the agents to a specific spatial location was identified as a "powerful tool for decision makers" by [15] (p. 14). [16] declare that the pedestrian simulation "has the potential to become the great success story for the application of agent-based simulation" [16] (p. 155) and define ABM as "the best, if not the only modelling paradigm for reproducing the reaction of travellers to locally displayed or dynamic information". On the other hand their results show that ABM has some disadvantages regarding the possibility to reproduce the results, as the models are not fully documentable, and because of sometimes high computational requirements.

[17] present a framework for simulating and evaluating individual pedestrian movements by examining various popular movement algorithms as motion controllers. Thereby, an extensive overview of movement algorithms classified by its scale (macro-movement on urban scale and micro-movement on person-scale) is given. As the macro-movement is not relevant for this work, two micro-movement algorithms as well as the respective results of [17] are shown in the following:

- Lévy-distributed walk [18]: "seems particularly well-suited to generating paths that ally with real-world human motion in dense urban settings" [17]
- Social force model [19]: "are also suitable for specific contexts (high density crowds in confined spaces) but do not work well in isolation" [17].

Regarding the movement of crowds as a whole, many studies were made concerning human behaviour during a panic or planned evacuation scenarios [20][21][22]. Beyond that, there are several studies working on crowd dynamics in normal situations. In the work of [23] the nature of crowds as well as their dynamics is examined and a model to simulate various scenarios are developed, which are successfully tested against several field studies. [24] observed crowd movement during the traditional Chinese spring festival in 2003 and suggested a crowd dynamics model based on "1) the front-back inter-person effect and 2) the pedestrian's self-driving motivation".

The estimation of pedestrian movement based on smartphone data was mostly limited to the macroscopic level based on mobility patterns derived from antenna signals with corresponding coarse cluster sizes [25][26][27]. Mainly due to privacy issues, the microscopic level is not yet fully studied. [28] presented an empirical study on human mobility based on 258 GPS traces from which the Lévy flight characteristics were derived and afterwards successfully reproduced using ABM.

The related work in the field of ABM revealed its high capability regarding pedestrian behaviour and movement in combination with GIS and geoinformation. Real-time remote sensing and in-situ sensor data may be included in an agent-based model to directly enhance the simulation process and results. On the other hand, the ABM results, based on real-time-data (e.g. single person trajectories derived from remote sensing imagery), could be used to predict the future situation and to identify

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probable ‘hot spots’, which might need further inspection and data acquisition. To study this potential an experimental test recording has to be performed.

3. Datasets and experimental setup

Studies concerning the combination of airborne imagery and in-situ sensor data often fail already in the recording phase, as the data have to be recorded simultaneously. Considering the process of flight planning and the weather conditions, there are a variety of factors that might disrupt concurrent data recording. Therefore, a simulated recording under defined test conditions was planned and conducted for this work. The preliminary goal is to evaluate the data quality of the in-situ sensor data concerning positioning and moving directions. Based on these results, the potential of agent-based modelling for the verification of people trajectories derived from image data can be studied.

The basic idea is the manual recording of image data series with a typical SLR camera from a high building to simulate airborne imagery. The spire of the Marienkirche in Osnabrueck (Germany) is chosen as an ideal recording platform as it is one of the highest buildings in the inner city of Osnabrueck (approx. 40 meters) and holds an observation deck with an almost clear view over the ancient market place of Osnabrueck. At the weekends and during major events in the inner city, this place is often crowded and therefore extremely capable for further test recordings as well.

The SLR camera used for the test recordings is a Nikon D5100 with a 16.2 megapixel CMOS sensor equipped with an AF-S DX 18-55 mm lens. In a first step, images with different focal distances (18, 35, 48 and 55 mm) were taken to analyze the varying distortions after the georectification in a later step. Focal distances of 48 mm and 55mm are the ones closest to typical airborne image recording systems whereas a focal distance of 18 mm increases the recorded area significantly.

Figure 1. Georectified images from the observation deck of the Marienkirche with different focal distances (left: 18 mm [zoomed in]; right: 48 mm).

In any case, the relatively low height of the recording platform (compared to aircrafts) results in a oblique view which is why the images have to be precisely rectified based on very accurate and reliable ground control points. Therefore, a TOPCON real time kinematic (RTK) differential GPS (dGPS) system is used. As the camera position is fixed, the acquisition of ground control points has to be done only once and allows for an automatic processing of image series.

Figure 1 shows two georectified images with different focal distances, 18 mm on the left and 48 mm on the right. The images are not orthorectified as the heights of different objects are not included. This results in an oblique view on buildings and objects in the recorded area. For this work, the images with the focal distances of 18 mm are used as on the one hand the study area increases significantly and on the other hand the distortion resulting from the varying focal distances seems apparently negligible. Due to the low recording height, both focal distances result in a highly sufficient image resolution.

The in-situ sensor data are recorded from test persons on the ground equipped with Samsung Galaxy S3 smartphones and Garmin GPSMap 60CSx hand-held GPS devices. The Samsung Galaxy S3 has a huge variety of built-in sensors like a 3-axis accelerometer, a 3-axis magnetic field sensor, an orientation sensor, a gyroscope sensor and many more [29], combined with the possibility to add geographic location from GPS. The Garmin hand-held GPS device serves as a second provider of the current position of the test person to validate the smartphone location recording.

The sensors of the Samsung Galaxy S3 can be accessed via Android programming interfaces [30]. Hence, an Android App was programmed and implemented to read and store the sensor data and the geographic location in a specific frequency which matches the recording frequency of the SLR camera (in this case: 1 Hz).

For the actual test recordings, the image and in-situ data have to be recorded simultaneously. Therefore, the internal clocks of the SLR camera, the smartphones and the Garmin GPS devices have to be synchronized. This allows for an easier post-processing and data calibration.

Afterwards, the actual positions of the test persons are gathered for each image individually of the image time series. The moving directions are derived based on the connection of two consecutive points. Based on that, the data quality of the in-situ sensor data concerning positioning and moving directions can be evaluated.

4. People trajectories from in-situ sensor data

The in-situ sensor data for this work are mainly based on the built-in smartphone sensors. The Android app therefore stores a variety of sensor data into separate CSV (comma-separated values) files. A Java program was written to visualize the recorded position data as well as their respective bearings.

Figure 2. Recorded Smartphone positions (yellow) and the positions derived from the image series data (red) from test person 1 (left) and test person 2 (right). The positions of the Garmin hand-held GPS (green) are shown for test person 2.

Beyond that, the recorded data are visualized in a GIS with the possibility to include base layers like the recorded image data. Figure 2 presents the recorded Smartphone positions (yellow) and the positions derived from the image series data (red) from test person 1 (left) and test person 2 (right). The tracks are roughly similar to each other although the smartphone positions apparently vary in their accuracy. This fact is supported by the positions of the Garmin hand-held GPS (Fig. 6: right, green). This should be more accurate than the GPS device of the smartphone, but it displays also differences from the actual positions (red). Hence, the deviation is not only affected by the smartphone’s GPS receiver but is apparently due to the conditions at the study area which in fact is surrounded by high buildings, leading to a small sky view factor. Taking this into account, the results of both the smartphone and the Garmin hand-held are reasonable. However, they are not suitable for a highly accurate single-person tracking.

Figure 3a illustrates a subset of positions and bearings of test person 2 (blue) and the derived positions from the image series data (red) with the respective moving directions. One can clearly see

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that the GPS positions are not very accurate as the test person starts the recording in front of the Marienkirche which results in a poor GPS signal. However, the bearings of the initial seven points are similar to the bearings derived from the image data. The mean value of those seven bearings differs only one degree from the first bearing of the image derived positions. It can be seen that the GPS accuracy does not significantly influence the accuracy of the bearing. Figure 3b supports this observation by showing the smartphone-measured positions (green) and bearings of test person 3 as well as the respective image-derived values (red). The difference between the bearings has a maximum of 10 degrees whereas the positions have higher variations. Therefore, it can be assumed that the in-situ measured bearings are quite sufficient for the verification of people movement directions derived from image series data.

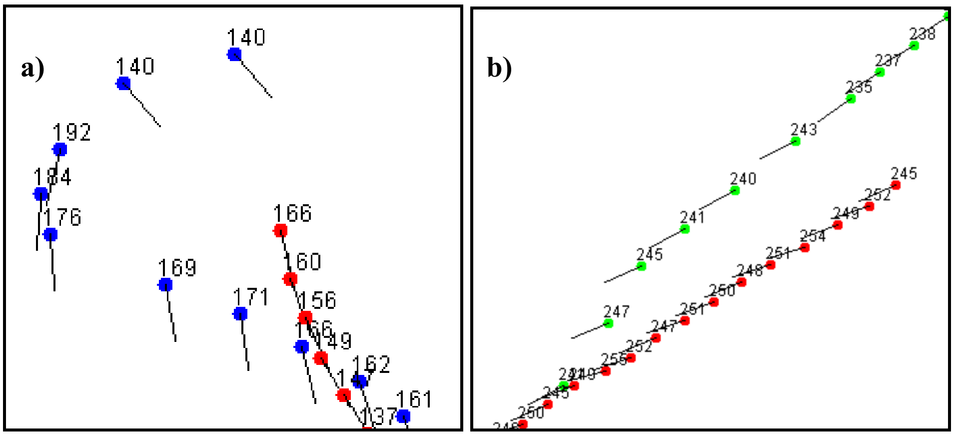

Figure 3. Positions and their respective bearings of a) test person 2 (blue: smartphone; red: extracted manually from images) and b) test person 3 (green: smartphone; red: extracted manually from images).

Based on these findings, the bearings derived from the in-situ sensor data can be included in an agent-based model to calculate new locations of agents at each time step. It should be considered to manage the influence of in-situ sensor data depending on data accuracy by using an impact parameter. This parameter adjusts the ratio of the bearing to the actual target of the agent and the current movement bearing. Furthermore it might be reasonable to smoothen the bearings by using mean values of the recent data points or to suppress bearings that are most likely outliers.

5. Conclusion and outlook

Based on the results of the simulated test recordings, it can be stated that the derivation of single people trajectories derived from image data for the prediction of crowd movement based on smartphone in-situ sensed movement data is promising and should be investigated and exploited further. Simulations on a microscopic level – as suggested in this study – are still rare. However, first studies show promising results by using GPS traces (e.g. [28]). Especially the combination of ABM and GIS technology allows for an actual spatial representation of the modelling parameters and results.

Depending on the results and the computation time of more complex spatial ABMs, an online system for real-time verification and movement prediction might as well be possible and should be put on the research agenda.

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