Monitoring Microscopic Pedestrian Mobility Using Bluetooth

Patrick Utsch
Knowledge Discovery
Fraunhofer IAIS
Sankt Augustin, Germany
Patrick.Utsch@iais.fraunhofer.de

Thomas Liebig
Knowledge Discovery
Fraunhofer IAIS
Sankt Augustin, Germany
Thomas.Liebig@iais.fraunhofer.de

Abstract—**Recently evolved Bluetooth tracking technology is currently applied to extract individual pathways, movement patterns or to rank popularity of locations by their visitor quantities. To utilize this technology for the creation of location aware intelligent environments, the next steps are to come up with microscopic traffic values. This work proposes a solution for this question, namely, a Bluetooth localization and path reproduction of individual persons. Our approach applies radio signal strength fingerprinting. We introduce and evaluate this approach for varying granularities and mobile phone types. The result is an accurate reproduction of pedestrian position and route choice in a complex facility.**

Keywords-Bluetooth Tracking; Location Awareness; Pedestrian Monitoring

I. INTRODUCTION

Major public events (concerts or sport events) attract thousands or millions of visitors within a comparatively short time period, whereas public buildings (e.g. airport terminals, train stations, shopping malls), parks or zoos reach the same amount of pedestrians within a much larger time period. While both scenarios seem to differ at the first sight, they have the uncertainty on people's preferences and motivations in common. Knowledge on people's presence, movement and behavior offers a vast chance for improvement of the signage and the infrastructure in order to create intelligent environments. Everything provided to the guests depends on the pedestrian movement. To give a few general examples: locations of information desks, shops or toilettes depend on the reachability and quantity of persons, path-widths of the corridors in a stadium depend on people's quantity as well, synchronization of digital signage and audio-guides depends on the average pedestrian speed, mobile phone networks are planned according to the expected movements and even locations of advertisement billboards are placed such that they achieve highest visit potential. Understanding the movement behavior, identification of attractors and distracters, determination of waiting times, as well as localization of congestions and bottle-necks gives indispensable insights on visitor preferences and motivations at a particular public event or site and thus supports creation of intelligent environments.

Currently used technologies to measure these highly needed movement data are surveys, video surveillances as well as the recently evolved Bluetooth tracking [1,2]. Whereas the first solution (surveys) is expensive and hardly representative due to the non-random sampling among all visitors, the second one (video surveillance) depends on the weather conditions, illumination and density of the people and does not seldom require special scaffoldings to carry the cameras. Bluetooth tracking overcomes all the mentioned shortcomings and offers a robust technology which can be applied seamlessly indoors and outdoors. Deployment of the required hardware is also fast and easy and, most of all, independent of the provided infrastructure. Thus, it is a perfect choice to monitor pedestrian mobility. Utilizing Bluetooth scanners for pedestrian tracking bases on a mesh of radio frequency sensors of certain diameters. Whenever a person with a Bluetooth enabled device (e.g. a mobile phone or an intercom) passes the footprint of a sensor, an entry is attached to a data-log storing the time-stamp, the position and a unique identifier for this person. Each sensor itself generates pedestrian counts. By use of multiple sensors, movement patterns and transition times are recorded. Expected representativeness is about 7 percent of the visitors [3]. The technology is already widely used for performance monitoring [4] which just depends on macroscopic movement values (e.g. people's quantities and densities). This work focuses on the task to monitor microscopic pedestrian mobility from a Bluetooth sensor mesh. Therefore the task is two folded: (1) exact localization of persons and (2) individual path reconstruction. Our approach utilizes fingerprinting technology as well as data mining methods to estimate the most likely position or path.

The paper is organized as follows. Section 2 introduces Bluetooth sensors and presents a summary of latest research on Bluetooth tracking. Furthermore this section presents state-of-the-art localization methods. In Section 3, localization is addressed. Our fingerprinting approach is discussed and performed in a test scenario. In this section, we compare different approaches and test them for accuracy. Section 4 addresses path reconstruction which was stated to be our second task. We summarize and conclude within Section 5 and give directions for future research.

II. RELATED WORK

Existing indoor tracking technologies are surveys and video surveillances. Whereas the first solution (surveys) is expensive and hardly representative due to the non-random sampling among all visitors, the second one (video surveillance) depends on the weather, illumination and density of the people and does not seldom require special scaffoldings to carry the cameras. In this section we present recent research on Bluetooth tracking. Afterwards we describe different position techniques. This also includes the radio signal strength based technique, which we are going to use in combination with the fingerprinting algorithm in the experiments within the next sections.

A. Bluetooth tracking

The need for further robust passive localization technologies pushed the development of sensors that are capable to monitor people's movement. First choice is to track most popular digital gadgets: mobile phones and intercoms. Analysis of mobile network GSM (Global System for Mobile Communications) log files [5] causes strong privacy objections. Besides, Bluetooth technology is an emerging technology for monitoring tasks [1,2]. Recently evolved Bluetooth based mobility sensors have been used for event monitoring at a soccer match in France [3] and a car race [4]. There, a mesh of Bluetooth sensors has been placed at carefully selected indoor as well as outdoor locations. The work in [3] extracts the route choices of the visitors and hands them to a agent based pedestrian microsimulation in order to extract microscopic movement values. In [4] formalization of recorded data is addressed. Similarities to other episodical movement data are presented as well as methods for their processing and visual analysis. Besides event monitoring, also other successful indoor applications of Bluetooth scanners are described in literature. In [6] various scanners were placed at Dutch train stations to record transit travelers. Accurate locating and following of objects within complex facilities is as well an important research topic [7].

So far Bluetooth tracking is used to monitor a sample of visitors [3,4,6] and extract their route choices [3]. In few works time-geography and movement patterns are addressed as well [8]. In contrast, we are going to extract microscopic values (pedestrian position and route choice) using Bluetooth scanners.

B. Localization technologies

For the determination of position using radio waves, different approaches exist. There are several position techniques, whose usage depends on the type of sensor. Furthermore there are different position algorithms which depend on the previously used position technique. A typical positioning system works as follows: A sensor retrieves a signal of a Bluetooth enabled device within reach. Using a position technique the values are processed and handed into the location algorithm. This estimates a position to the retrieved signal [9].

We give an overview on the most common position techniques. Angle Of Arrival (AOA) computes the angle between the mobile phone and the sensor. With increasing distance this position technique becomes more imprecise due to the simultaneously increasing precision requirements. With two sensors an angulation based position algorithm can be applied. Time Of Arrival (TOA) records the time it takes for a signal to be sent from a sensor to a mobile phone or vice versa. Having multiple sensors, a trilateration algorithm can be applied to extract positions. In this case, larger distances cause a higher precision. Radio Signal Strength (RSS) uses the dependency of radio signal strength on the distance. In theory they carry an inverse proportional relation. RSS is easy to use; in contrast to TOA and AOA no additional data processing is required. Similar to TOA the position may be estimated using trilateration algorithm. The Bluetooth scanners used in this work are not capable of measuring neither angles nor precise time differences, but record a radio signal strength value. Thus, we use a RSS localization technique. Furthermore, we utilize the location fingerprinting algorithm which is a pattern matching algorithm that estimates the position based on training data. It consists of two phases: an online and an offline one. During the online phase signal strengths are recorded for various training locations. In case of noisy environment, these perturbances are recorded directly with this data and do not require further filtering. In the online phase a data mining model (trained with the data from the offline phase) is used to match a position for a current radio signal strength value. The next sections study this algorithm for use with Bluetooth data and present our performance analyses.

III. PEDESTRIAN POSITION REPRODUCTION

In this section we describe the use of the fingerprinting method for Bluetooth pedestrian position reproduction in our test scenario and introduce the results of this attempt. In this context we collect training data, build up different types of prediction models and validate the performance.

For easy validation, our experiments are performed within a lab of size 10 times 15 meters. The room includes some furniture and separating walls (see Fig. 1 for a floorplan image) that may affect the radio signal strength (RSS) in terms of increased noise factor. Four Bluetooth sensors are uniformly distributed among the room, and thus placed in each corner. Therefore, the footprints of the sensors overlap. The problem of long scan intervals of the Bluetooth protocol is addressed by usage of three antennas per sensor which scan simultaneously time shifted for Bluetooth enabled mobile phones. As radio signal strength depends directly on the distance, localization

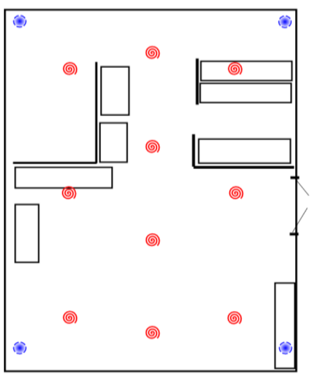

Figure 1. Floorplan of the test field; dots mark the sensor positions, helices mark the locations for training data recordings

techniques based on RSS may be studied in our test scenario.

For the pedestrian position reproduction, we utilize the fingerprinting method. This fingerprinting method can be divided into two stages, (1) an offline and (2) an online phase. During the offline phase, radio signal strengths become recorded as training data using well known devices at few well known, preselected, probing locations. As result we achieve a radio signal strength value at every probing location for all pairs of (sensor, mobile phone). The vector of all signal strength values for a mobile phone at one position (i.e. the set of values among all sensors) form the so called fingerprints for the probed locations. Based on these fingerprints a classifier is trained that predicts locations based on an arbitrary radio signal fingerprint. Any data mining method (e.g. k-Nearest Neighbour KNN or Support Vector Machines SVM) is applicable. Afterwards, in stage 2, the online phase, the previously trained model is applied to estimate current positions of devices based on their actual fingerprints. Since we are interested in localizing Bluetooth-enabled phones, we conduct our experiments with three HTC phones and one Nokia mobile phone. In step 1, we place it at ten different positions uniformly distributed in the room. The online phase, i.e. the application of the prediction model, will be used for pedestrian route choice reproduction, tackled in Section 4.

The distance between two positions ranges from 3 to approximately 4 meters. Figure 1 depicts the floorplan including the four sensor positions represented by blue points and the 10 probing positions for test recordings as red dots. During data acquisition at each testing location (indicated by red dots) the fingerprints of all mobile phones are recorded. Additionally the room is tessellated into various grids of different grain size to measure the prediction accuracy at different granularities later on. To each grid cell one or more test locations are mapped.

Analysis of the collected data indicates an irregular time interval between two succeeding records of one mobile phone to one sensor larger than one minute in marginal case but with an average of eight seconds approximately. The recorded signal strength data of each sensor is aggregated for every minute so that every sensor collects the same amount of data for each measurement position. Gaps in this aggregation (minutes without a data record for a particular mobile phone) are filled with the average of this mobile phones sensor data at this particular position.

The data-mining methods used in the training phase are K-Nearest-Neighbour (KNN) and Support Vector Machine (SVM). KNN compares the radio signal strengths with similar signal strengths of already predicted data by computing the euclidean distance and makes a discrete classification for a grid cell, as well as a probability value for each grid cell based on its the weighted nearest neighbours. SVM performs a linear binomial classification by computing a line with the largest possible distance between two classes. As we have more than two classes multiclass SVM is used by comparing one versus all each time. Experiments have shown that KNN gives the better prediction results as seen in Table 1, thus from now on KNN is used for our prediction.

During the validation process three different versions of the k-fold cross validation are considered. One version with the standard leave-one-out method (1), one version where instead of one record, the whole data of one mobile phone is left out (2) and one version where only the data of one mobile phone is observed, using the leave-one-out method again (3). Motivation for this is to take a look at the influences of different mobile phones, as experiences show that in intelligent environments many different phone-types are used and people carry their phones at different positions. For the 10-position grid the leave-one-out method has an accuracy of 67.95%, the leave-one-phone-out method has 50.23% and the leave-one-out with just one phone an accuracy of 73.64%. To consider the different phone types in a real environment we just look at the leave-one-phone-out method in the following predictions. Table 2 shows the prediction results for different grids.

The “2-grid top bottom” divides the room in two cells – top and bottom – and for each probing position (red dots in Figure 1) it is predicted if it belongs to the upper or to the lower grid cell. Not all recorded positions are used as training data; it is differentiated between only the upper and lower corner-points, three points including the top/bottom middle point and four points including additionally the position close to the center. The “2-grid left right” divides the room in a left and a right grid cell, one time with just the corner-positions as input another time also with the particular center positions. The “3-cell grid” divides the room in an upper, middle and a lower cell, each time using only the respective left and right position as input. The “4-cell grid” consists of four corner cells with just the corner-position as input. The “6-cell grid” divides the room in 6 cells. This can be equalized with the 6 positions, each 3 left and right, not using any middle positions.

As we can see the 10-position prediction with accuracy of 50.23% is not very good. Especially the four center-near positions deliver unsatisfactory results. By coursing the grid, the results become better. Considering just the top bottom and the left right grid we have a probability larger than 90% for positions near the sensors. Once the positions are farther away the results degrade but still have an overall accuracy of more than 80%. The nearer the positions are to the next grid-cell the more the prediction accuracy decreases.

In the next step we take a look at the impact of the number of sensors on the accuracy and therefore we remove each sensor once and make the prediction. As a result, the prediction worsens in every experiment, most in the corner where the

TABLE I COMPARISON OF KNN SVM FOR LOCATION REPRODUCTION

Grid	KNN	SVM
10-position grid	50.23%	38.41%
6-cell grid	71.21%	64.02%
4-cell grid	94.89%	90.34%

TABLE 2 LOCATION REPRODUCTION ACCURACY

Grid	Leave-one-phone-out
10-position grid	50.23%
6-cell grid	71.21%
4-cell grid	94.89%
3-cell grid	78.41%
2-grid top bottom, 2 points	97.73%
2-grid top bottom, 3 points	91.67%
2-grid top bottom, 4 points	83.81%
2-grid left right, 2 points	93.75%
2-grid left right, 3 points	81.44%

omitted sensor is missing. Afterwards we add a fifth sensor near the left-middle position. The prediction accuracy for the “6-cell grid” improves about 15% especially at the left middle cell where the new sensor is placed. The “10-position grid” improves about 13% and the “3-cell grid” about 11%. On the other hand the “2-grid top bottom” decreases by 2% and the “4-cell grid” by 1%. This shows that using more sensors does not per se guarantee better results for each type of prediction. Moreover, results depend on the placement strategy of the sensors in balance with the places we want a fine granularity of localization estimation.

In conclusion, the tests have shown that a localization estimation for distances of less than 4 meters do not give results that are good enough for use in real environments with different mobile phone types. However, these results are quite good when using only a single phone, especially when a fifth sensor is placed at a strategic position. Considering larger distances by dividing the room in just two halves top/bottom or left/right or in sensor near quarters we get robust results that are suited for real world applications and creation of pedestrian location aware intelligent environments.

IV. PEDESTRIAN ROUTE CHOICE REPRODUCTION

Creation of location aware environments does not only need to identify current pedestrian positions but identification of their routes taken through a particular site. In this section we introduce the pedestrian route choice reproduction which we base on the position prediction models from the previous section. This includes the definition of routes, the collection of training data, two different attempts of data preparation and the creation and validation of route prediction models. We close this section with the evaluation of our approach.

For the pedestrian route choice reproduction a graph is mapped to the floorplan, containing different possible predefined routes. These routes can be clustered in different complicacy levels, defined 'left route', 'right route', 'top route', 'bottom route' as well as more difficult routes leading through the center of the room. Figure 2 visualizes the graph in our floorplan, and the routes can be seen as black arrows in Figure 3. For the validation a person walks the routes in different speed – extremely slow or normal – using the Nokia mobile phone. Only the models with data of the Nokia phone as input as well as five sensors placed in the room are used as they have shown in the previous Section 3 to deliver best usable location estimations for the 10-position test grid.

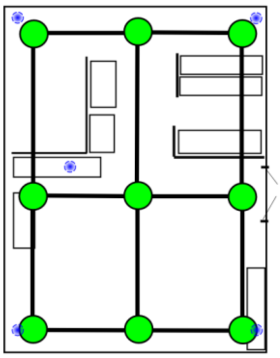

Figure 2. Floorplan of the test field with mapped graph for route choice reproduction in green

Two different types of data preparation are performed. The first one merges the sensor data whenever data from at least three or more sensors is available within a 10-second interval. These aggregation intervals may overlap, thus it is possible that one record may belong to several entries. Each entry obtains the average time of the involved sensors. The second data preparation method interpolates between previous and next signal strength record, e.g. two entries with signal strength 70 and 60 and 9 seconds time between them generate 9 new database records labeled with signal strength from 61 to 69. However, afterwards we have a signal strength value for each sensor at every second.

Next the positioning models from the previous section are used to predict a position to each data record. Besides the discrete positions each result gets as well a fuzzy prediction based on KNN percentage results. The 10 position probabilities and the grid-cells are mapped to the graph and by that a chosen route can be predicted by the occurrence of each position. By comparing the prediction results of the two different prepared data sets it reveals that the version with interpolated seconds delivers slightly better performance. Therefore only this version is presented in the following examination.

In a first analysis the route prediction is studied taking the whole graph into account. Therefore, the 10-position model is used and each position is mapped to a graph node by its fuzzy prediction. The results for the slow routes are presented in Figure 3. As we can see route 4 (right) and route 5 (top) are predicted very well. However other routes behave worse although a trend to the correct route can be seen in most of the cases. Route 3 (center) is predicted well due to the effect that the predictions are equally distributed left and right, but on the other hand the center positions are usually not well predicted. Furthermore, the worse prediction of the center bottom node as seen at route 6 and 7 is particularly noticeable. Reasons could be the phone position or the change of furniture between the test experiments and the route prediction experiments.

In a second analysis the route prediction is observed taking only the routes 'left', 'right', 'top' and 'bottom' into account. By doing this we want to see how the results improve when we use larger distances between the routes. For this the prediction

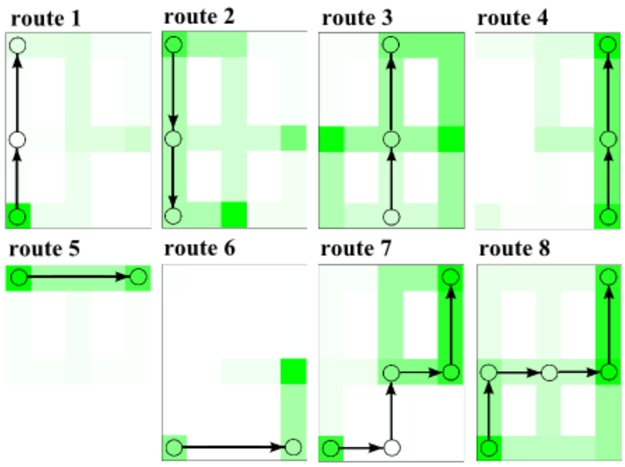

Figure 3. Results of route choice reproduction for eight test cases

models '2-grid top bottom' and '2-grid left right' are used. Table 3 illustrates our results.

These predictions give 100% correctness for all slow routes and just one error for the normal routes where the left route is predicted completely wrong. This is caused by few data entries at this point. In all other cases the 2-grid left right has correct predictions with a percentage from 74,94% to 91,62% (table values multiplied by 2) when we just take this grid-model into account. The 2-grid top bottom grid delivers even better results between 96% and 100%. As we make use of both models for the route prediction and not only top or bottom respectively left or right the mentioned percentages of 74.94% or 96% are the same results as seen on 2-grid left right for the slow left way and 2-grid top bottom for the normal bottom route multiplied by two.

Concluding the route prediction with an average route distance of about 3 meters, taking the 10-positon grid into account has not proven to deliver good predictions. However, classification with larger grid cells and a distance of approximately 6 meters produces good predictions. Disadvantage of this approach is that it does not provide an opportunity to predict time-related trajectories. Furthermore routes with the use of multiple mobile phones should be considered as well in future studies.

V. Conclusion and Future Work

This paper focused on pedestrian position and route choice reproduction. This task is of high interest for creation of location aware intelligent environment. Since existing technologies (video surveillance, surveys, light beams) have drawbacks and are not easy to apply, we studied the usage of Bluetooth tracking. We presented state-of-the art research for Bluetooth tracking and preceded the research on utilizing the fingerprinting method for Bluetooth tracking. Furthermore, we studied and validated performance and accuracy of the presented approach. Therefore, we used grids with varying granularity to evaluate the accuracy of our estimation depending on required precision. Afterwards, the pedestrian route choice prediction bases on the positioning model. The set of routes are predefined by a graph and the previously introduced grid-cells are mapped to its edges for prediction.

We have shown that it is possible to deliver good results for a smaller distance (3 to 4 meters) with the use of just one mobile phone and an expedient sensor positioning in relation to the positions we want to predict. However, models built not just for a lab but for real world usage need to perform well for different types of mobile phones. In our case, it was unusable for the fine granular grid. By taking a look at larger distances like predicting left and right or top and bottom of the room, which relates to 6 or more meters, we could get much better results. The results get better the nearer a position is to a sensor. Furthermore we have seen that the placement and amount of sensors can affect the result strongly. Therefore it is important to place sensors strategic depending on the goals. Taking the routes into consideration it is advisable to define grids as well as probing positions (where training data is recorded). Route predictions with a precision of 6 meters or more and the use of larger grid-cells have proven to deliver good results with a single mobile phone.

Future work should consider well defined relations between routes, grid-cells, sensor positions as well as collection of training data and its amount. In a further step the prediction of connected routes including time-related trajectories with the possibility to predict changes in direction and duration of stay should be integrated. This should also include the usage of multiple mobile phones. Another open task is the study of representativeness of Bluetooth tracking in detail.

References

[1] R. Fuller, Mobile Entity Localization and Tracking in GPS-less Enviroments. In: Tutorial on Location Determination by RF Means, Springer Berlin Heidelberg, 2009, pp 213-243

[2] R. Bruno and F. Delmastro Design and Analysis of a Bluetooth-based Indoor Localization System}, Proceedings of the 8th International Conference on Personal wireless Communication, 2008, pp 711-725

[3] T. Liebig and A. U. Kemloh Wagoum, Modelling Microscopic Pedestrian Mobility Using Bluetooth, Proceedings of the 4th International Conference on Agents and Artificial Intelligence, 2012, pp 270-275

[4] N. Andrienko, G. Andrienko, H. Stange, T. Liebig and D. Hecker, Visual Analytics for Understanding Spatial Situations from Episodic Movement Data, In: KI - Künstliche Intelligenz, Springer Berlin Heidelberg, 2012, pp 1-11

[5] F. Gianotti and D. Pedreschi, Mobility, Data Mining and Privacy - Geographic Knowledge Discovery, Springer, 2008

[6] M. Pels, J. Barhorst, M. Michels, R. Hobo and J. Barendse, Tracking people using Bluetooth. Implications of enabling Bluetooth discoverable mode, University of Amsterdam, 2005

[7] M. Nilsson, J. Hallberg and K. Synnes, Positioning with Bluetooth, Proceedings of the 10th International Conference on Telecommunication, 2003, pp 954-958

[8] H. Stange, T. Liebig, D. Hecker, G. Andrienko and N. Andrienko, Analytical Workflow of Monitoring Human Mobility in Big Event Settings using Bluetooth, Proceedings of the 3rd International Workshop on Indoor Spatial Awareness, ACM, 2011, pp 51-58

[9] K. Kolodziej, Local Positioning Systems: LBS Applications and Services. CRC Press, Boca Raton, 2006.