INDOOR LOCALIZATION AND TRACKING OF WIRELESS DEVICES

Master Course
Scientific Reading in Computer Networks

presented by

Danilo Burbano
2015

Head of Group:
Professor Dr. Torsten Braun
Institute of Computer Science
University of Bern

Contents

Chapter 1

Introduction

Indoor localization and tracking of wireless devices with high accuracy have been high intensive research works in recent years, because it is the foundation to achieve reliable support location-based services for indoor environments. Indoor positioning allow the development of various mobile and pervasive applications, such as advertisement promotion in airports or shopping malls, location detection of assets in a warehouse, patient tracking inside the building of a hospital, navigation during emergency rescue and emergency personnel positioning in a disaster area.

In contrast with outdoors, where solutions like Global Position System (GPS) can be used for localization, indoors environments have low accuracy using such techniques, especially GPS where the signals cannot penetrate in-building materials. Thus, several research work have focused on analysing different solutions like Pedestrian Dead Reckoning (PDR) systems along with WiFi components to increase the accuracy of RSSI approaches. Other works use Channel State Information (CSI) to have a more reliable source of information than RSSI, which leads to build a find-grained model between distance and wireless signal power, whereas for tracking systems some works focus on fusing PDR models and WiFi information with Bayesian Filters to improve the tracking accuracy of the mobile target.

Chapter 2

WiFi Indoor Localization

Most of research done about WiFi based indoor localization has shown that Received Signal Strength Indicator (RSSI) is easily affected by multipath effects and Non-Line Of Sight (NLOS) propagation, which leads to significant performance degradation. Hence, RSSI is not a reliable source of information to use as a metric for indoor localization. Consequently in order to tackle the issue of multipath propagation in indoor environments, some research has focused on analysing Orthogonal Frequency-Division Multiplexing (OFDM), because this digital multi-carrier modulation method offers benefits for localization and tracking. For instance, OFDM is spectrally efficient, so it provides very high data rates, which is very useful for any mobile and wireless communication scenario, and additionally the most important fact is that in OFDM the data to be transmitted is split across all the subcarriers to give resilience against selective fading from multipath effects.

Channel State Information (CSI) is used in OFDM to measure the channel at the subcarrier level, e.g. to support MIMO operation. Thus, CSI is a fine-grained value from PHY layer which describes the amplitude and phase of channel contention on each subcarrier in the frequency domain. Here is where CSI has become an interesting subject of research as a reliable metric for indoor localization, because it provides a much richer source of information than RSSI. Channel Impulse Response (CIR) is a systematic way to categorize channnels and has been used in works such as [9] to characterize the individuals paths of the communication channel in the time domain as a set of temporal linear filters. Therefore, CIR is not more than CSI but in the time domain.

WiFi-based indoor localization, can be classified as active localization systems and passive localization systems:

Active Localization: In active localization systems, targets are required to actively participate in the localization process as in [8] which is a work based on CSI to alleviate multipath effects at the target node, which receives the Access Point, i.e. anchor nodes, coordinates. In this work the frequency diversity of the subcarriers in OFDM systems is explored, in order to achieve fast and accurate indoor localization of the target node. Signal processing techniques are leveraged in both time and frequency domains to mitigate the multipath effects. Range-based localization is done using a refined indoor propagation model, where the environmental parameters of such model are retrieved by applying a fast training algorithm based on supervised learning, whereas the location determination, i.e. trilateration algorithm, is done by the receiver through aggregation of the CSI values from the physical layer to triangulate the precise position of the target object using a linear least square (LLS) method. Experimental results showed that the accuracy and latency of distance calculation can be significantly enhanced by using CSI, where for instance some positions with serious multipath effects achieve up to 10 times accuracy gain over the corresponding RSSI-based scheme. In average this solution outperforms RSSI around 3 times for the distance determination of a single link, and the median accuracy of this work is 1.2 meters.

Passive Localization: In passive localization systems, the targets do not need to participate in the localization process as in [9] where USRP receivers, i.e. anchor nodes, are used to extract CIR at the physical layer through Software Defined Radio (SDR) techniques. In this work the range-based localization algorithm is done with nonlinear regression (NLR) models, where the measurement parameters are converted into propagation distances based on a relationship with the CSI values as a nonlinear curve fitting problem, which improves the ranging accuracy compared to the commonly used log-distance path loss model (LDPL). The environmental parameters used in the NLR model defined by authors are obtained through algorithms to solve unconstrained optimization problems, in particular the trust region approach is applied in this work. For the location determination a new two-stage trilateration algorithm is proposed by the authors, which is a combination of Weighted Centroid and Constrained Weighted Least Square (WC-CWLS) methods. This combination is done with the aim of mitigating the influence of ranging (NLOS) errors. Experimental results showed that the algorithm is robust against ranging errors and outperforms the linear least square (LLS) algorithm and Weighted Centroid (WC) algorithm. The mean localization error of the system achieves 2.4 meters.

The main drawback in active localization systems is the intrinsic software and hardware limitation of target nodes. Despite the fact that in some works [8] a good accuracy is achieved, in practice with a high quantity of heterogeneous devices is rather difficult to have all targets with enough computation capabilities to process the algorithms to locate itself. Furthermore, under the assumption that the targets have enough capabilities, there is the issue of the battery, which implies a time constraint for such solution, because the battery can be depleted much faster than in a passive localization solution. Additionally, in active localization systems, whenever a software modification is needed, it would require an update in every single target node, whereas for passive localization systems the update could be done just in the anchor nodes or in a central server where the localization algorithms are running. Therefore, in passive location systems the deployment and support is easier than in active localization systems.

The main drawback in passive localization systems, is the higher cost such systems could incur [9], because it is needed to have specialized hardware in the anchor nodes. Thus, this solutions are recommended for third party companies interested to enter the positioning service sector.

Chapter 3

Pedestrian Dead Reckoning

Pedestrian Dead Reckoning (PDR) is a process originally taken from navigation, where dead reckoning is used to estimate the position, orientation and velocity of a target without external references. PDR exploits the readings of off-the-shelf Inertial Measurement Units (IMUs) embedded in smartphones and has been used along with GPS for map-matching i.e. outdoor tracking. In positioning systems PDR is used to estimate displacement step by step of a pedestrian user by combining step detection, stride length and heading direction estimation. There are several works that have adopted PDR as an important component for tracking, where the displacement of the pedestrian user is estimated through inertial sensors such as accelerometers, magnetometers and gyroscopes. Based on the techniques used in those works, it would be possible to classify PDR solutions as Sensor Fusion and Full Sensor Fusion. The former refers to works where the orientation of the smartphone is known and the latter refers to works where the orientation of the smarthpone is estimated.

Sensor Fusion: These works made use of the readings from accelerometers and gyroscopes to estimate the displacement of a pedestrian user under the assumption that the way a pedestrian user is holding the smartphone is constant. In [4], [5] the heading direction estimation of the user is based on the measures from the gyroscope, whereas the displacement of the user is estimated only with accelerometer values.

Full Sensor Fusion: These works made use of the readings from accelerometers, magnetometers and gyroscopes to estimate the displacement of a pedestrian user, and in addition these works also derive the orientation of the smartphone while it is carried during walking. In [1] accelerometer and magnetometer are used to estimate the device orientation, then a walking and running model is built based on accelerometer measures, whereas principal component analysis (PCA) of the horizontal acceleration is used to estimate the moving direction. Other works [2] make use of the gyroscope to distinguish between random device's orientation changes and physical turns of the pedestrian user. In this work the distance estimation is made with the measures of the accelerometer and the moving direction is estimated with a combination of the measures from the gyroscope and magnetometer. Some works [3] merged the methods detailed above to estimate the device orientation, and use the accelerometer not only for step detection but also to determine heading direction of the user by combining accelerometer readings with the readings from the magnetometer and gyroscope.

Unfortunately, inertial sensors from smartphones are very noisy because of the low cost IMUs embedded in those devices. Thus, PDR based on smartphones have some drawbacks such as accumulation of errors and noise. For instance, in the gyroscope we can have cumulative errors because this inertial sensor reads the value of the angular velocity. Therefore, integration over time of the angular velocity is needed in order to estimate the angle, whereas the magnetometer is very sensitive to interference from other magnetic fields, making it really difficult to find the earth's magnetic field needed to identify the true north, especially for indoor environments, where it is possible to find a lot of different materials and electrical devices that can generate magnetic fields, which disturb the magnetometer readings.

There are several mechanisms used to reduce the noise and cumulative errors from the raw data taken from smartphone's inertial sensors such that we can get more reliable data. For instance the data from the accelerometer can be processed with a low pass filter, which is enough to implement an algorithm for step detection and distance estimation.

In order to reduce the noise in the magnetometer there are some mechanisms [6] where the accelerometer is used to compensate the magnetometer readings whereas hard-iron effects are identified to subtract magnetic fields within the vicinity of the magnetometer leading to more accurate data. For solutions where the gyroscope is used, the magnetometer can be used to mitigate gyroscope errors [7].

The main drawback for using approaches with the magnetometer is that getting reliable data to estimate the heading direction of a user in indoor environments is complex because in such scenarios the earth magnetic field is going to be superimposed by many other magnetic fields, additionally it is distorted by nearby ferrous materials that are commonly found in buildings, markets, airports, etc. Therefore, it is really necessary to include accelerometer or gyroscope information to correct the magnetometer measures as well as compensations mechanisms to reduce the offset generated by nearby magnetic fields such that it is possible to achieve reliable data.

The main drawback for using approaches with gyroscope is that although it is relatively immune to environmental disturbance, the accumulation of errors can increase without a bound even after some drift reduction mechanisms, specially when the walking takes a considerable time. There are some algorithms implemented as in [5] to tackle the problem of accumulation based on a dynamic feedback drift elimination but is not practical because it requires specialized sensors in the foot of the pedestrian.

Chapter 4

WiFi Indoor Tracking

Most of the positioning algorithms for indoor localization (see chapter 2) do not consider mobility, which normally works well for static targets, but for mobile targets it is required to adopt some tracking schemes such as pedestrian dead reckoning (see chapter 3). However in order to tackle the intrinsic dead reckoning errors that still persist even after applying some noise and drift reduction techniques, some suitable mechanisms have to be taken into account to further improve the accuracy. Several works [1], [2], [3] make use of Bayesian filters (e.g. Kalman Filter, Particle Filter), because such filters allow easily modelling a dynamic system from sensor measurements. Several works have shown that by combining dead reckoning with Bayesian filters the accuracy of the model is considerably increased.

Particle filters are able to estimate the parameters of a system (e.g. user location) using Bayesian principles. Unlike a Kalman filter, particle filters are easily adapted to handle the presence of obstacles like walls, non-linearities and non-Gaussian noise models, multiple hypotheses, etc. without special extensions to the filter. This is particularly important when such a wide variety of sensing types are being combined. A particle filter will usually be more computationally expensive than a Kalman filter, but they can still work with reasonable speed on a smartphone processor. In contrast to Kalman filter, the performance of a particle filter can be scaled with available computation power by varying the number of particles that are tracked. A particle filter has 3 major components:

- Motion Model: This model is in charge of updating the positions of particles.
- Observation Model: This model is in charge of setting particle weights.
- Re-sampling Algorithm: This algorithm is used for modifying the distribution to reduce variance.

One can see in works such as [10], where a tracking system is implemented by exploiting particle filters to combine dead reckoning, RSS-based readings and knowledge of floor plans together. Authors in [10] implemented a PDR component in a smartphone that outputs a human motion vector model, which is then use as input for the particle filter component, whereas WiFi component records RSS values periodically from all available APs in the floor as a RSS vector.

In addition authors in [10] exploit RSS readings through comparative analysis of the relationship between the RSS values during the motion of a pedestrian, concluding in three observations:

- Turn Verifying: It is used to handle unconscious human behaviours that cause great change on the readings of direction sensors, for instance hand trembling while a pedestrian user is walking. RSS vectors between continuous steps are examined to distinguish pedestrian turning from hand trembling.
- Room Distinguishing: It is used to distinguish which room the pedestrians enter when two doors are close to each other. When a pedestrian user is entering a room, there is a clear tendency in the change of RSS vectors.
- Entrance Discovering: It is used to try to discover a possible path when the estimated position remains almost the same while particles keep dying for a number of steps.

The aim of adopting particle filters [10] is to represent and control uncertainty of PDR, leveraging the constraints imposed by floor plan and the indication of the WiFi component. The particle filter component redistributes every particle according to the motion vector in propagation phase. Then, the correcting phase first corrects the weight of each particle according to the floor plan and calculates the weighted center of the particles. Upon the geometric relationship between the new center and last tracking position, the particle filter component invokes Turn Verifying, Room Distinguishing and Entrance Discovering of WiFi component to further correct the particle weights. The resampling phase follows and outputs the center of weighted particles as the current estimated location of the pedestrian. Authors in [10] used an active localization system based on three major components: PDR, WiFi and Particle Filter, where the particle filter component is installed in off-the-shelf smartphones, thus the number of particles is limited, although the system achieves a good localization error of 0.71 m in a college building covering 1362 m^2.

Another work as in [3] proposes an application for robust WiFi indoor tracking by combining complementary localization approaches for dead reckoning and WiFi signal strength strategies. The complementary and redundant characteristics of the two approaches allow the system to operate robustly even in environments where one or more individual sensors maybe disrupted. The system makes use of RSSI for position estimation. In addition a fingerprinting technique is used to establish a relation between RSSI and position. Furthermore, once a calibration database of the environment has been generated, it can then be used across different smartphones without the need for re-calibration. Authors make use of WiFi radio combined with PDR for use in the system. This approach combines multiple complimentary localization systems including dead reckoning, WiFi, and GSM using a particle filter for robust localization over multiple floors of an indoor building. A walking motion model combined with a heading estimator provides a pre-filtered dead reckoning sensor estimate to the particle filter. The combined sensor data is fused and filtered using a particle filter which results in a smooth and continuous position estimation state. At runtime WiFi signal strength fingerprinting is used to initialize the system and it provides a rough global location estimate. The user's movement is also tracked at high frequency using dead reckoning. Authors in [3] introduce a particle filter to combine these different sources of information. To minimize the computational requirements of the solution, authors focus on keeping the dimensionality of the particle filter as low as possible. For this reason, authors do not track heading within the filter, but estimate only the linear position. The dead reckoning is performed in a pre-processing step, and all the particles in the filter are periodically updated based on a model of the variance of the dead reckoning estimate. Experimental results are analysed using an online system and an offline system. In the former the algorithms ran in the smarthpone, whereas in the latter the smartphone just collected the data, which is afterwards processed by the algorithms in a laptop. The average mean error of the system is 3 m.

The main drawback of [10] is that a prior knowledge of the floor plan and coarse distribution in which room the APs resides is required. Therefore this solution has not a high scalability, although it is better than RSS fingerprint works as in [3], in which locations of APs are exacted and RSS fingerprint database is required.

The main drawback of [3] is that WiFi signal strength fingerprinting approach requires a calibration step, even though authors claimed this can be speeded up using a robot for mapping a floor. There are some works [10], where a calibration phase is not required. Thus, deploying this solution is not a trivial task and is more costly.

Chapter 5

Conclusions

Based on works as in [8] and [9] CSI information is highly recommended for ranging models, where it is possible to achieve a fine-grained relation between transmission power and distance. Even though in some works [10] and [3] reasonable accuracy is obtained just with RSSI, several obstacles can be found in most real indoor environments, which certainly leads to multipath effect issues. Thus, a more refined range-based localization model is required. Furthermore, an intensive site survey is not required in CSI works, which implies a more easy to deploy and scalable approach than RSSI.

PDR motion models can be designed using different inertial sensors, the aim to achieve a reliable data is to apply filters to the raw data and to fuse information from different sensors. In addition it is really important to take into account mechanisms to identify noise and drift reduction of the raw data. In many cases considerable errors still persist due to error accumulation, and Bayesian filters can be used to improve the accuracy. In [10] particle filter is adopted as its core to represent and control uncertainty in dead reckoning. When applying these observations on RSS, authors in [10] correct the accumulated error of dead reckoning to achieve high accuracy.

Particle filter is very useful for indoor tracking because it offers two main advantages. First it is able to handle non-linear models such as range-based localization for CSI [9]. Second, particle filter allows data fusion, which means that different source of information like RSSI, CSI, PDR can be used to estimate the position of a target with high accuracy.

Bibliography

[1] N. Kakiuchi1 and S. Kamijo, ”Pedestrian Dead Reckoning for Mobile Phones through Walking and Running Mode Recognition”, in Proceedings of the 16th International IEEE Annual Conference on Intelligent Transportation Systems (ITSC 2013), The Hague, The Netherlands, October 6-9, 2013.

[2] A. Mariakakis, S. Sen, J. Lee and K. Kim, ”SAIL: Single Access Point-Based Indoor Localization”, in MobiSys’14, June 16-19, 2014, Bretton Woods, New Hampshire, USA.

[3] N. Kothari, B. Kannan and M. B. Dias, ”Robust Indoor Localization on a Commercial Smart-Phone”, The Robotics Institute, Carnegie-Mellon University, August 2011.

[4] F. Hong, H. Chu, L. Wang, Y. Feng and Z. Guo, ”Pocket Mattering: Indoor Pedestrian Tracking with Commercial Smartphone”, in International Conference on Indoor Positioning and Indoor Navigation, 13-15th November 2012

[5] J. Borenstein and L. Ojeda, ”Heuristic Drift Elimination for Personnel Tracking Systems”, in The Journal of Navigation 2010.

[6] T. Ozyagcilar, ”Implementing a Tilt-Compensated eCompass using Accelerometer and Magnetometer Sensors”, in Freescale Semiconductor, Rev. 3, 01/2012.

[7] M. H. Afzal, V. Renaudin and G. Lachapelle, ”Use of Earth’s Magnetic Field for Mitigating Gyroscope Errors Regardless of Magnetic Perturbation”, in Sensors 2011, ISSN 1424-8220.

[8] K. Wu, J. Xiao, Y. Yi, M. Gao, and L. M. Ni, ”FILA: Fine-grained Indoor Localization”, in INFOCOM, 2012 Proceedings IEEE

[9] Z. Li, T. Braun, D. C. Dimitrova, ”A Passive WiFi Source Localization System based on Fine-grained Power-based Trilateration”, in IEEE International Symposium on a World of Wireless, Mobile and Multimedia Networks (WoWMoM), 2015.

[10] F. Hong, Y. Zhang, Z. Zhang, M. Wei, Y. Feng and Z. Guo, ”WaP: Indoor Localization and Tracking Using WiFi-Assisted Particle Filter”, 39th Annual IEEE Conference on Local Computer Networks, LCN 2014, Edmonton, Canada.