Indoor Positioning Systems using Wi-Fi

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ABSTRACT

Indoor Positioning Systems (IPS) are used when GPS doesn't work or is unreliable. Technologies such as Bluetooth Low Energy beacons, Wi-Fi or Geomagnetic mapping are considered as alternatives. In this paper we will introduce the theme to the reader and overview some state of the art approaches to build IPS systems. In particular, we have focused on Wi-Fi fingerprint-based positioning system and their recent techniques.

Keywords

IPS, GPS, Wi-Fi

1. INTRODUCTION

Indoor Positioning Systems (IPS) locates people or objects inside a building using radio waves, magnetic fields, acoustic signals, or other sensory information collected by a smartphone, tablet or other smart devices. IPS can be used to develop location-based apps and other features. Even though the most commonly used location technology is the Global Positioning System (GPS) it is not suited for IPS, because it suffers from several problems, such as signal blockage and the radio signal may also reflect off the surrounding environment causing low accuracy. Because of this the indoor location market is where other technologies have the most impact. There are three mainstream types of IPS that organizations or individuals implement in their indoor spaces, either exclusively or together as a hybrid solution to provide more accuracy, these include, Bluetooth Low Energy (BLE) beacons, Wi-Fi and Geomagnetic. Most smartphones between 2010-2017 have the hardware capabilities to use any of these technologies, using their Wi-Fi chipset, Bluetooth chipset or their magnetometer.

Geomagnetic uses a building magnetic field to create a magnetic field map. However, if only magnetic field map navigation is used, the estimated position can have large errors and every time an object that interferes with the buildings/room geomagnetic signature is introduced the map has to be recreated (H.-S. Kim, Seo, and Baek 2017).

BLE beacons are small devices that emit a radio signal over a time period, this period is called the refresh rate. Normally this time period is set to around 1000 milliseconds to save battery life, but can be adjusted to ranges from 50 milliseconds to 5000 milliseconds depending on the device manufacturer. The device uses a protocol to emit its data, Eddystone made by Google or the iBeacon made by Apple are the most commonly used, both are open standard. Several proprietary protocols also exist.(Cerruela García, Luque Ruiz, and Gómez-Nieto 2016). The different protocols between manufactures add an extra layer of complexity to this technology and as of yet no standard protocol exists. Because the device is battery based, the signal will fluctuate with direct proportion to the battery level. This makes it difficult to get an accurate position of an object or person.(Cerruela García, Luque Ruiz, and Gómez-Nieto 2016)

Wi-Fi technology is used to communicate over a wireless network by using a radio signal typical in the 2.4GHZ to 2.4835GHZ range for the European Union. Hardware for this technology follow the IEEE 802.11 standards. With the increase usage of the Internet, public and private access points are increasingly popular, combined with the fact that almost all smartphones have Wi-Fi capabilities it provides a very good starting point for an IPS based on a single technology.

Even though it does not depend on batteries the the Received Signal Strength Indication (RSSI) still fluctuated over time. But unlike BLE beacons most or all of the infrastructure is already implemented almost everywhere. The protocol for communication is also standardized so IPS solutions based on this technology only have to follow one standard. It does however still suffer from magnetic interference, especially when used only with a fingerprinting based or RSSI based techniques. It is the focus of this paper to analyze the various IPS techniques using Wi-Fi technology.

2. State of the Art

Wi-Fi positioning systems are divided into two categories, one is based on radio signal propagation and relies on computing distances between mobile devices and points whose coordinates are known. The second one is based on mapping by combination of RSSI measurements and geographical coordinates, called a RSSI map. Locating a mobile device with a RSSI map consists in matching a measurement with some point of the SS map. Measurements matching is either deterministic or probabilistic. (Cypriani et al. 2010)

2.1 Radio Signal Propagation

In radio signal propagation approaches, the main problem is to calculate distances between the Access Points (Aps) receivers based on RSSI values. Distance calculations requires radio wave propagation modeling to be able to judge the distance according to the RSSI value. After calculating the distances towards surrounding APs, a mobile device can compute its location through multilateration. When using Multilateration it should be taken into account the error in distance calculation. (Cypriani et al. 2010)

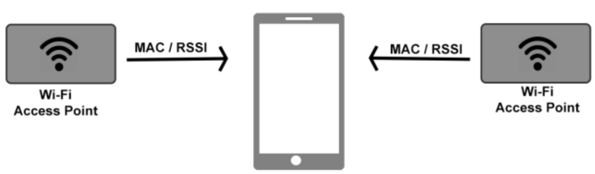
2.2 Mapping RSSI Values

RSSI map systems are based on mapping by combining the geographical coordinates and RSSI values. Geographical coordinates can be expressed in cartesian (x,y,z) coordinates, or GPS coordinates (latidude and longitude or degrees, minutes and seconds).

There are two steps RSSI map-based systems:

First an offline training step builds an RSSI map by measuring the RSSI value in different places, this implies moving physically to every location in the map and perform a measurement or by using simulations. While moving physically gives real measurements, it requires a lot of time. On the other hand, building the map by simulation requires a lot of work to build a propagation model (Mazuelas et al. 2009). Simulating radio signal propagation to build an RSSI map will rely on propagation-based positioning systems techniques. However, there is a key difference between the two systems: a radio signal propagation based positioning system doesn't know the smartphones location, therefore it cannot take into account the obstacles between the mobile and the transmitters (Cypriani et al. 2010). Mapping associates RSSI values to known geographical coordinates. It is able to take into account the obstacles with models like that of Motley-Keenan.(Cypriani et al. 2010)

For the second step, the online positioning step relies on the RSSI map previously built, and uses it to matches the received value measurement to the value map content. Matching can be either deterministic or probabilistic. Deterministic matching uses the RSSI directly to cross reference with the map in which each location has a list of access points within range and an average value of signal strength for each Access Point (AP). Probabilistic matching requires more data in the RSSI map. Values must be described by a probability distribution. Then, matching is achieved by probabilistic methods based on Gaussian models like the CMTA (Baala and Caminada 2006) or the kernel method (Roos et al. 2002).



3. Wi-Fi Fingerprint Advanced Algorithms

The methods mentioned before represents traditional ways to develop basic systems (Bahl and Padmanabhan 2000). The RSSI vectors in traditional methods can lead to inaccurate positions due to measurements noise (Xiao, Wen, Markham, Trigoni, et al. 2015), for this reason, researchers have proposed several algorithms that take into account temporal or spatial observations, which can be categorized into the following areas: 1) temporal and spatial signal patterns; 2) collaborative localization; and 3) motion-assisted localization.

Temporal patterns are when a target is moving in a building, the Wi-Fi signal of the AP follows a pattern. The signal and the trajectory of the route can be used to infer the location. In this category, was introduced two schemes Walkie-Markie (Shen et al. 2013) and PWF (Y. Kim, Hyojeong Shin, and Cha 2012), the difference between them, is that PWF considers only the peak signal as counterpart which considers all the RSSI sequence, both need additional information (walking direction) and presents a reported mean approximately 2 meters of accuracy. PWF by considering only the peak, represent one limitation when the user is moving quickly.

The spatial patterns are related to signal distribution, which takes aspects such as signal coverage, landmarks, and RSSI order. This category requires signal investigation in site to find remarkable values to uniquely identify regions, forming this way, the landmarks. Hallway (Jiang et al. 2013) and UnLoc (Wang et al. 2012), both use this technique to localization. Hallway, in specifically, takes all AP's signal strength in a respective area, sort them out, to form a pattern which can be correlated. To clarify the algorithm, consider three AP with respective signal {s1,s2,s3}. On a room A the signal strength may be manifested as { s3 < s1 < s2 }, the pattern may uniquely identify the respective room.

The usage of the Hallway is aimed to room classification, even though, is unreliable under rooms that have signals strength approximately equal. The scheme offers a mean of 90% of accuracy in finding corrects rooms. UnLoc corrects localization by taking certainly identifiable in a specified zone, it needs walking trajectory information and as a mean of 2 meters of accuracy.

Collaborative localization is another recent category of algorithms proposed by researchers. They came out with the same purpose, reduce the error, with promising results (Jun et al. 2012; Banerjee et al. 2010). They take information from another sensor(s) such as Bluetooth, sound, WIFI Direct, etc, to identify nearby users. We can categorize into to distance and proximity-based schemes.

On distance-based scheme, a graph is formed with the computed distance between users, this pairwise information is gathered from the sensor in order to build the graph topology. On this category, we have Virtual Compass (Banerjee et al. 2010), Peer Assisted (Liu et al. 2012) and Centaur (Nandakumar, Chintalapudi, and Padmanabhan 2012). VC is based on Vivaldi Algorithm to infer the spatial space of the targets which are related, thus, to mitigate the error in radio measurements it fuses Bluetooth and WI-Fi Direct. Requires that targets remain statically positioned, and is not applied for absolute localization. The other two schemes use sound sensor instead, which offers more accurate distances between the targets. Beep technique is used in PA for distance measurements. The cluster of targets collects all RSSI values, which is used to estimate the location of each, then, along with peer sound measurements, the information is transformed into a network graph, with the goal of minimizzing all Euclidean distances from the stored Wi-Fi signal map. The Centaur has the same philosophy, the only difference is that uses probabilistic method to collaborative localization. Both schemes offer high robustness of distance measurements and accuracy, however, they were designed for static devices and assume that targets form a clusters, in other words, that persons as social beings form cluster.

In proximity category, was proposed ZCL and Social-Loc schemes, they might use Wi-Fi AP list, Bluetooth, Wi-Fi Direct to infer target proximity. ZCL (Chan et al. 2006), specifically uses ZigBee radio as the neighbor-detection which identifies nearby targets as possible candidates for collaborative localization, they computes a confidence score to the estimated position and finally, adjusts the estimated location of closest targets with higher confidence scores. Social-Loc (Jun et al. 2012) also uses at first moment the Wi-Fi fingerprint-based localization and define events such as “meeting” and “missing” for each target(s) (reference points), in other words, if two targets encounter each other, is defined “meeting” event and their localization must be overlapped, if the candidate position does not meet with the event information, the event is filtered. Those two schemes do not offer high accuracy, for ZCL is crucial that users must be close to each other and the Social-Loc the thresholds of the events can be difficult characterization due to the noise.

The last reviewed category is motion-assisted localization. They already are present in our daily lives, for instances, fairly all today's smartphones can estimate how many steps that we have take or gestures that we do, or even where we are looking at. Those devices are equipped with microelectromechanical systems (MEMS), which that we commonly refer as accelerometers, gyroscopes, and magnetometers. The information from MEMS along with Wi-Fi fingerprint can be used to fuse into an algorithm to determine the target’s localization.

The researchers in recent works have studied three components on the usage of the Pedometer (step counter) : 1) walking direction; 2) step count, and 3) stride fast measurements. This study was required due to the heterogeneity of movements patterns that the user may manifest in their walking trajectory, also the sensor requires some sort of calibration, notably in works (He et al. 2015; Xiao, Wen, Markham, and Trigoni 2015) a particle filter (Arulampalam et al. 2002) learning or expectation maximization is used to step length calibration.

The challenging part of the motion-assisted category is to create reliable models that merge all sources of information. The traditional sensor fusion tries to find the target’s localization and reduce the error that may come with Wi-Fi fingerprint systems, in other words, has the same goal of the two previous categories already mentioned. However, over the time, AP’s can be substituted or removed producing on inconsistencies on the stored data, and newer offline training are required, which can be expensive to conduct. As a response to, a more complex approach is needed. The academia classifies this problem as Simultaneous Localization and Mapping using Wi-Fi and motion information. The idea is that we can track a target while reconstructing the map information.

Kalman filter already is used in GPS to fuse sensors information, one particular situation, for example, is when a user is traversing a tunnel and the GPS signal might be lost for a short period, and by applying this filter an estimation of the exact position can be made. In this category was proposed Zee (Rai et al. 2012) and Moloc (Sun et al. 2013). Zee uses particle filter, basically it uses an optimal estimation algorithm used to estimate states of the system from indirect and uncertain measurements, it uses it has a localization algorithm and requires steps count and heading direction as motion information. Do not require calibration, and the training data is gathered from the targets. The weakness of Zee is that the crowdsourced signal data may carry noise, however, shows robustness under narrow corridors. The reported mean of accuracy is 2m.

Maloc propose a more efficient way of locate the target by reducing the number of particles and implement simplified probabilistic models, Hidden Markov Model (Seitz et al. 2010) respectively. It uses maximum likelihood or fingerprint and motion as localization algorithm, and as Zee, requires step count and heading direction, thus crowdsource motion profile. One difficulty of implement Maloc is the necessity of knowing user motion profile, however, it has a reported mean of less than 1m.

To conclude, this last category is more appealing than collaborative localization, they do not require the knowledge of the relative targets, offering higher adaptability and scalability, one aspect to consider is the energy efficiency.

4. Conclusion and Further Work

The indoor location problem is not solved, despite the advanced algorithms in a fingerprint-based location that we have reviewed,

none of them reported accuracies that are acceptable for many industries. For instances, on the retail market with one-meter accuracy, the target can be surrounded by a dozen products, making impractical to applications such as dynamic personalized pricing, and product placement and advertisements. Although, for noncritical applications, the combination of them can produce acceptable results. Nonetheless, the implementation of one IPS systems with underneath techniques requires a careful study to meet the requirements, this is, each scheme reviewed, was their weakness and strengths, some may perform better for room classification and other open environments such as airports.

Another important aspect is the efficiency on deployment of this kind of systems, this was not reviewed and deserves proper investigation. To conclude, building a practical Wi-Fi-based indoor positioning system is a challenging task, the academia has not yet biased for one typical solution offering this way a diversity of techniques to recreate the experience of GPS.

5. REFERENCES

Arulampalam, M. Sanjeev, Simon Maskell, Neil Gordon, and Tim Clapp. 2002. “A Tutorial on Particle Filters for Online Nonlinear/Non-Gaussian Bayesian Tracking.” *IEEE Transactions on Signal Processing* 50 (2):174–188.

Baala, O., and A. Caminada. 2006. “WLAN-Based Indoor Positioning System: Experimental Results for Stationary and Tracking MS.” In , 1–4. IEEE. https://doi.org/10.1109/ICCT.2006.341742.

Bahl, P., and V.N. Padmanabhan. 2000. “RADAR: An in-Building RF-Based User Location and Tracking System.” In , 2:775–84. IEEE. https://doi.org/10.1109/INFCOM.2000.832252.

Banerjee, Nilanjan, Sharad Agarwal, Paramvir Bahl, Ranveer Chandra, Alec Wolman, and Mark Corner. 2010. “Virtual Compass: Relative Positioning to Sense Mobile Social Interactions.” *Pervasive Computing*, 1–21.

Cerruela García, Gonzalo, Irene Luque Ruiz, and Miguel Gómez-Nieto. 2016. “State of the Art, Trends and Future of Bluetooth Low Energy, Near Field Communication and Visible Light Communication in the Development of Smart Cities.” *Sensors* 16 (11):1968. https://doi.org/10.3390/s16111968.

Chan, Li-wei, Ji-rung Chiang, Yi-chao Chen, Chia-nan Ke, Jane Hsu, and Hao-hua Chu. 2006. “Collaborative Localization: Enhancing WiFi-Based Position Estimation with Neighborhood Links in Clusters.” *Pervasive Computing*, 50–66.

Cypriani, Matteo, Frederic Lassabe, Philippe Canalda, and Francois Spies. 2010. “Wi-Fi-Based Indoor Positioning: Basic Techniques, Hybrid Algorithms and Open Software Platform.” In , 1–10. IEEE. https://doi.org/10.1109/IPIN.2010.5648232.

He, Suining, S.-H. Gary Chan, Lei Yu, and Ning Liu. 2015. “Calibration-Free Fusion of Step Counter and Wireless Fingerprints for Indoor Localization.” In , 897–908. ACM Press. https://doi.org/10.1145/2750858.2804254.

Jiang, Yifei, Yun Xiang, Xin Pan, Kun Li, Qin Lv, Robert P. Dick, Li Shang, and Michael Hannigan. 2013. “Hallway Based Automatic Indoor Floorplan Construction Using Room Fingerprints.” In , 315. ACM Press. https://doi.org/10.1145/2493432.2493470.

Jun, Junghyun, Long Cheng, Jun Sun, Yu Gu, Ting Zhu, and Tian He. 2012. “Improving Indoor Localization with Social Interactions.” In *Proceedings of the 10th ACM Conference on Embedded Network Sensor Systems*, 323–324. ACM.

Kim, Han-Sol, Woojin Seo, and Kwang-Ryul Baek. 2017. “Indoor Positioning System Using Magnetic Field Map Navigation and an Encoder System.” *Sensors* 17 (3):651. https://doi.org/10.3390/s17030651.

Kim, Yungeun, Hyojeong Shin, and Hojung Cha. 2012. “Smartphone-Based Wi-Fi Pedestrian-Tracking System Tolerating the RSS Variance Problem.” In , 11–19. IEEE. https://doi.org/10.1109/PerCom.2012.6199844.

Liu, Hongbo, Yu Gan, Jie Yang, Simon Sidhom, Yan Wang, Yingying Chen, and Fan Ye. 2012. “Push the Limit of WiFi Based Localization for Smartphones.” In *Proceedings of the 18th Annual International Conference on Mobile Computing and Networking*, 305–316. ACM.

Mazuelas, Santiago, Alfonso Bahillo, Ruben M. Lorenzo, Patricia Fernandez, Francisco A. Lago, Eduardo Garcia, Juan Blas, and Evaristo J. Abril. 2009. “Robust Indoor Positioning Provided by Real-Time RSSI Values in Unmodified WLAN Networks.” *IEEE Journal of Selected Topics in Signal Processing* 3 (5):821–31. https://doi.org/10.1109/JSTSP.2009.2029191.

Nandakumar, Rajalakshmi, Krishna Kant Chintalapudi, and Venkata N. Padmanabhan. 2012. “Centaur: Locating Devices in an Office Environment.” In *Proceedings of the 18th Annual International Conference on Mobile Computing and Networking*, 281–292. ACM.

Rai, Anshul, Krishna Kant Chintalapudi, Venkata N. Padmanabhan, and Rijurekha Sen. 2012. “Zee: Zero-Effort Crowdsourcing for Indoor Localization.” In *Proceedings of the 18th Annual International Conference on Mobile Computing and Networking*, 293–304. ACM.

Roos, Teemu, Petri Myllymäki, Henry Tirri, Pauli Misikangas, and Juha Sievänen. 2002. “A Probabilistic Approach to WLAN User Location Estimation.” *International Journal of Wireless Information Networks* 9 (3):155–164.

Seitz, Jochen, Thorsten Vaupel, Jasper Jahn, Steffen Meyer, Javier Gutierrez Boronat, and Jorn Thielecke. 2010. “A Hidden Markov Model for Urban Navigation Based on Fingerprinting and Pedestrian Dead Reckoning.” In , 1–8. IEEE. https://doi.org/10.1109/ICIF.2010.5712025.

Shen, Guobin, Zhuo Chen, Peichao Zhang, Thomas Moscibroda, and Yongguang Zhang. 2013. “Walkie-Markie: Indoor Pathway Mapping Made Easy.” In *Proceedings of the 10th USENIX Conference on Networked Systems Design and Implementation*, 85–98. USENIX Association.

Sun, Wei, Junliang Liu, Chenshu Wu, Zheng Yang, Xinglin Zhang, and Yunhao Liu. 2013. “MoLoc: On Distinguishing Fingerprint Twins.” In , 226–35. IEEE. https://doi.org/10.1109/ICDCS.2013.41.

Wang, He, Souvik Sen, Ahmed Elgohary, Moustafa Farid, Moustafa Youssef, and Romit Roy Choudhury. 2012. “No Need to War-Drive: Unsupervised Indoor Localization.” In *Proceedings of the 10th International Conference on Mobile Systems, Applications, and Services*, 197–210. ACM.

Xiao, Zhuoling, Hongkai Wen, Andrew Markham, and Niki Trigoni. 2015. “Robust Indoor Positioning with Lifelong Learning.” *IEEE Journal on Selected Areas in Communications* 33 (11):2287–2301.

Xiao, Zhuoling, Hongkai Wen, Andrew Markham, Niki Trigoni, Phil Blunsom, and Jeff Frolik. 2015. “Non-Line-of-Sight Identification and Mitigation Using Received Signal Strength.” *IEEE Transactions on Wireless Communications* 14 (3):1689–1702. https://doi.org/10.1109/TWC.2014.2372341.