Scene Analysis based Bluetooth Low Energy Indoor Positioning Methods

Master's Thesis Proposal v0.5

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1 Introduction

The field of indoor positioning system (IPS) came to existence due to poor performance of traditional global positioning system (GPS) indoors due substantial signal attenuation leading to uncertainty spanning several rooms and sometimes the whole floor. Thus, the need for a better and cheap solution arose. Previously, the technologies like Assisted GPS, Micro-Electro-Mechanical (MEMS) systems, Light Emitting Diodes (LED), Wireless Fidelity (WiFi), Visual Light Communication (VLC) etc., or methods in conjunction with each other were used. The IPS takes advantage of sensor hub present in the smart phones and also the external sensor information like motion detection using pyro-electric infrared (PIR) sensor for improving the accuracy and efficiency of IPS.

Indoor positioning systems (IPS) problem poses a different challenge right from the type of the indoor setting, technology leveraged to methodology used for solving the problem. For example, in the case of bluetooth low energy (BLE) technology, which utilizes received signal strength indicator (RSSI) from the signal advertised for positioning, even the orientation of the BLE chip installed can drastically affect the accuracy of the positioning system in addition to usual multipath and signal attenuation. Hence, a detailed study of IPS is inevitable.

The aim of this thesis is to 1) develop an automatic node location identification (ANOLI) algorithm and 2) develop an BLE based indoor positioning algorithm. The setup considered is as follows. The BLE beacons are part of densely packed intelligent luminaires, the nodes (or beacons) can also read the signal strengths from neighboring nodes. Generally, a location estimation task involves two hardware devices, one transmitting the signal, the beacon and other receiving it, the mobile unit (MU) [3]. Here, the transmitting device is bluetooth low energy chip installed in ActiveAheads. The ActiveAheads are intelligent predictive lighting solution which learns based on experience and are part of a mesh network. We use beacons and nodes interchangeably in the rest of the document.

2 Goal of the thesis:

1. **Automatic Node Location Identification (ANOLI):**

   Primary task:

   The aim of the task is to intelligently find the locations of the beacons on the floor plan. As already said above, the state-of-the-art ActiveAhead can simultaneously advertise and read the bluetooth low energy (BLE) signals. The received signal strength indicator (RSSI) value which is the central component of the signal is planned to be leveraged along with other sensor data for achieving this. To aid this task, we plan to pin-point the location of the gateway (master ActiveAhead) and tag related beacons to it to simplify the task.

   Secondary task (optional):

   The aim of this task would be to get the metadata after combining all the sensor information and create a topology of the sensors. This metadata would include the beacons' location along with relative location to a landmark on the floor, cluster to which it would belong, where the cluster node is the gateway. Hence, this task could also be named **Self Organizing Sensor Network** [11]. The feasibility study is yet to be done for this task.

2. **Bluetooth Low Energy Indoor Positioning (BLE-IP):**

   The aim of this RSSI based task is to develop an algorithm for indoor positioning using the BLE technology. This task also plans to make use of RSSI value from the BLE signal. We plan to record the measurements using the demo android application developed in-house to test different algorithms based on hypothesis generated from the experiments. The outcome of the ANOLI task and other sensor data (optional) would be used to make positioning algorithm more accurate.

3 Related Work

The main challenge for BLE-IP task is getting a right data model as the RSSI values are attenuated based on various factors. The probability distribution of the recorded RSSI values can be either be left skewed, right skewed or symmetric based on the indoor structure, this is because RSSI values is a function not only of location but also of time. Log-normal, Gaussian and exponential were different models which were successfully fit [16]. The variety of smartphone hardwares and it's handling also exace rbates the issue of modeling. Next we discuss the RSSI based algorithms.

3.1 RSS based Localization Algorithms

3.1.1 Triangulation

Triangulation includes methods like Lateration and Angulation. These are signal attenuation based models (RSS based) which try to learn the path loss component due to propagation and as the signal in indoor setting is degraded due to multipath fading. Different methods include time of arrival (TOA), time difference of arrival (TDOA), round trip of flight (RTOF). These methods requires estimates from at least three different known sources and they suffer badly due to lack of line of signal. In angulation, the target's located is estimated using angle from at least two reference points.

3.1.2 Static Scene Analysis (Fingerprinting)

Scene Analysis involves inferring based on features already recorded for a particular location and static scene analysis looks up into a pre-recorded dataset which maps locations with it features [25]. Hence, it is also called *fingerprinting* as it aims at creating unique feature map based on location dependent measurements. This method involves matching the measured signal with location-dependent ground truth signal via a radio map. The localization can be accomplished using Bayesian Filters (Grid Filter, Kalman Filter, Extended Kalman Filter, Unscented Kalman Filter) and Sequential Monte Carlo methods like Particle Filter. These algorithms can be used in conjunction with other deterministic and probabilistic schemes like k-Nearest Neighbors or Gaussian Processes (Latent Variable Models).

Advantages of scene analysis over other methods is that it doesn't require any additional information about the beacons in contrast to triangulation methods [25]. And, these methods are scalable when used in conjunction with GP's [25]. One other advantage is when using semi-parametric models (GP's) here, is that with enough evidence the non-parametric counterpart can override the parametric one's [15]. One drawback of fingerprinting based method is that indoor setting is restructured or locations of nodes is changed then the current radio-map would become redundant, needing a new radio-map [4].

Few challenges plaguing RSS based methods are enumerated below:

1. Multipath and fading.

2. Movement of user causes fluctuation called small scale fading [14].

3. Heavy interference due to 2.4 GHz license-free frequency which is also used by cordless phones, bluetooth devices, WiFi signals and microwaves [5].

4. Signal attenuation based on presence of number of people. This is because human bodies are bags of waters which can adsorb signals [5].

5. Absence of ping from any BLE device due to malfunction can effect the positioning accuracy.

4 Methods and Materials

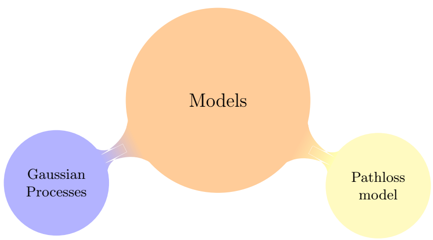
4.1 Methodology in the thesis

In this thesis we concentrate on different models and methods. Models are either Gaussian Processes (GP) or Pathloss model. Gaussian processes can be used both during the fingerprinting phase or as the measurement likelihood (or data) model. Pathloss model could be inaccurate as the signal suffers from multiple attenuations indoors so inclusion of prior knowledge is crucial here. So the pathloss model is used in conjunction with either GP for bettering the accuracy. The methods are described next.

4.1.1 Different kinds of Methods

1. **Non-memory based methods** (NMM): These methods are deterministic or intelligent methods which try to relate the spatial space with the signal space. These methods are Trilateration/ Triangulation, k-Nearest Neighbors, Artificial Neural Networks etc. These methods estimate directly based on the RSSI values with no knowledge about the previous state or previous measurements, hence the name Non-memory based methods.

2. **Memory based methods (or Sequential Bayesian Filtering)** (MM): By adding a dynamic model or the prior to the non-memory based methods we arrive at Memory based methods which are also called Sequential Bayesian Filtering methods. The non-memory based methods are used as the measurement model, hence combining with the prior knowledge we arrive at an possibly accurate posterior or state estimate.



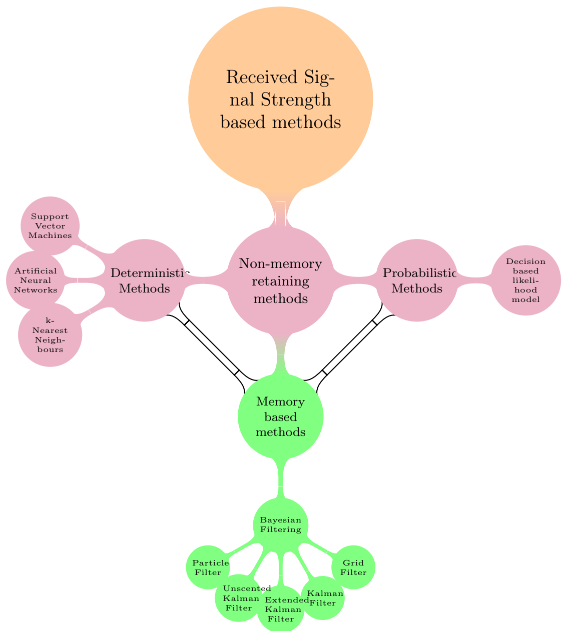


Figure 1: (left) Gaussian Processes and Pathloss models used in the thesis. (right) RSSI based methods used in the thesis. The colorless edges denote that memory based methods can be used in conjunction with non-memory based methods.

5 Plan

Month	Aim	Tasks
February	REST API	Completed
Meeting 1	Slides:	https://goo.gl/Up9ejx
March	1. Proposal 2. Literature Review	1. Make extensive notes of the reading 2. Will move it to thesis 3. Make plan.
	Phase 1	
April	1. Proposal 2. ANOLI	Week 1: Finalized proposal Week 2, 3: Update the existing code for ANOLI. Week 4: Complete ANOLI
May	1. Get better model 2. Implement methods	Week 1: Buffer Period Week 2: Buffer Period Week 3: Update Android application for experiments (5.1.1.a-5.1.1.c). Week 4: Collect initial data, analyze, run NMM's
June	1. Get better model 2. Implement methods	Week 1: Run the MM's Week 2: Buffer Period Week 3: Update Android application for next experiments (5.1.1.d-5.1.1.e). Week 4: Collect data, analyze, run NMM.
July	1. Get better model 2. Implement methods	Week 1: Run the MM's Week 2: Buffer Period Week 3: Update Android application for next experiments (5.1.2-5.1.4). Week 4: Collect data, analyze, run NMM
August	1. Get better model 2. Implement methods	Week 1: Run the MM's Week 2: Buffer Period Week 3: Buffer Period Week 4: Buffer Period
	Phase 2	
September October Novemeber	Writing	1. Compile results, write it to thesis, and survey paper. 2. Polish the thesis,comments from instructor and supervisors.

Table 1: Plan for the thesis

5.1 Experiments: Data Analysis of RSSI values.

1. Different Biases in RSSI measurements

   (a) User's presence: We would experiment measuring the RSSI values with and without user's presence.

   (b) Smart-phones: We would like to understand how different hardwares in the smartphone affect the RSSI values.

   (c) Orientation of phones: We would like to understand how different angles, height of usage of smartphones would affect the RSSI measurements. Also, measuring while being still in 4 cardinal positions and while rotating.

   Hypothesis: 5 dBm difference for the change in orientation [14].

   (d) Material of luminaires: Since the luminaires of different material (metal, plastic, metal+plastic) are used, we would like to see how much bias is added because of this.

Its added bonus if we get the luminaire material information from the BLE signal.

(e) Orientation of Bluetooth module: The bluetooth modules are embedded inside the luminaires and can have different orientation. We need to record the RSSI values in all the cardinal directions with chip either facing upwards and downwards.

2. Calibration time: It is the time for which we measure the RSSI values for the creating the reference database. Here, we would consider normal phone usage conditions (tilted phone at chest height).

3. Different calibration points: How many calibration points are required for the reference database for getting maximum accuracy. Any criterion on how to select these locations?

4. Malfunctioning BLE chip: How would our algorithm perform when one or many BLE chips send out weird RSSI values? First, we would manually manipulate the data to change the RSSI values of nearest nodes in our dataset and experiment it. Based on the results we would like to increase the number of malfunctioning nodes.

References

[1] Yeqing Fang, Zhongliang Deng, Chen Xue, Jichao Jiao, Hui Zeng, Ruoyu Zheng, Shunbao Lu, "*Application of an Improved K Nearest Neighbor Algorithm in WiFi Indoor Positioning*," China Satellite Navigation Conference(CSNC), 2015 Proceedings: Volume III2015342, Berlin, Germany, Springer 517524, Lecture Notes in Electrical Engineering, 10.1007/978-3-662-46632-2_45, doi:10.1155/2014/649276

[2] Xianghui Yuan, Feng Lian, and Chongzhao Han, "*Models and Algorithms for Tracking Target with Coordinated Turn Motion*," Mathematical Problems in Engineering, vol. 2014, Article ID 649276, 10 pages, 2014. doi:10.1155/2014/649276

[3] H. Liu, H. Darabi, P. Banerjee and J. Liu, "*Survey of Wireless Indoor Positioning Techniques and Systems*," IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), vol. 37, number 6, 1067-1080 pages, Nov 2007, doi:10.1109/TSMCC.2007.905750

[4] Yiu, H. Darabi, P. Banerjee and J. Liu, "*Locating User Equipment and Access Points using RSSI fingerprints*," IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), vol. 37, number 6, 1067-1080 pages, Nov 2007, doi:10.1109/TSMCC.2007.905750

[5] Arjun. P. Kamath,"*Indoor Location-Based Services In The Telecommunications Network*", Master Thesis, Department of Communications and Networking, School of Electrical Engineering, Aalto University, 2014.

[6] B. Ferris, D. Fox, and N. Lawrence. WiFi SLAM Using Gaussian Process Latent Variable Model. In JCAI, January 2007.

[7] Beacon, link: https://store.kontakt.io/our-products/30-double-battery-beacon.html.

[8] Discussion with Max Björkgren on 9th March.

[9] Martin Sauter (2010). "3.7.1 Mobility Management in the Cell-DCH State". From GSM to LTE: An Introduction to Mobile Networks and Mobile Broadband (eBook). John Wiley & Sons. p. 160. ISBN 9780470978221.

[10] http://www.geospatialworld.net/wp-content/uploads/magazine/Geospatial-World-August-2014.pdf.

[11] Discussion with Tommi Raivisto on 16th March.

[12] Project done for the course CS-E4030 - Seminar on Gaussian processes, School of Science, Aalto University.

[13] Suining He, S.-H. Gary Chan. *"Wi-Fi Fingerprint-based Indoor Positioning:Recent Advances and Comparisons"*, IEEE Communications Surveys and Tutorials, 2015.

[14] Kaemarungsi et al, Analysis of WLAN's received signal strength indication for indoor location fingerprinting,2011

[15] Philipp Richter, Revisiting Gaussian Process Regression Modeling for Localization in Wireless Sensor Networks, 2015.

[16] Honkarvirta et al, 2009;

[17] De Luca et al, Performance evaluation of Indoor Localization Techniques Based on RF Power measurements from Active or Passive Devices.

[18] Hightower et al, Location Sensing Techniques, A Technical report, 2001

[19] Mazzullah Khan et al,2017

[20] Umar Ahmad, iBeacon Localization, Master Thesis.

[21] Smailagic et al, 2002

[22] Prasithsangaree et al, 2002

[23] Torres-Sospedra et al, A realistic evaluation of indoor positioning systems based on Wi-Fi fingerprinting, 2017

[24] Nurminen et al, Particle Filter and smoother for Indoor localization,2013

[25] Hightower et al, Location Sensing Techniques, A Technical report, 2001