

Scene Analysis based Bluetooth Low Energy Indoor Positioning Methods

Master's Thesis Proposal v0.4

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1 Introduction

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 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. So, 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. Previously, many deterministic and probabilistic methods have been deployed and this thesis aims to test the important methods and select the one which performs well for our setting which described next.

1.1 Setup

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 Active Aheads. The Active Aheads are part of a mesh network.

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. So, 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 exacerbates 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 Lateralation 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.

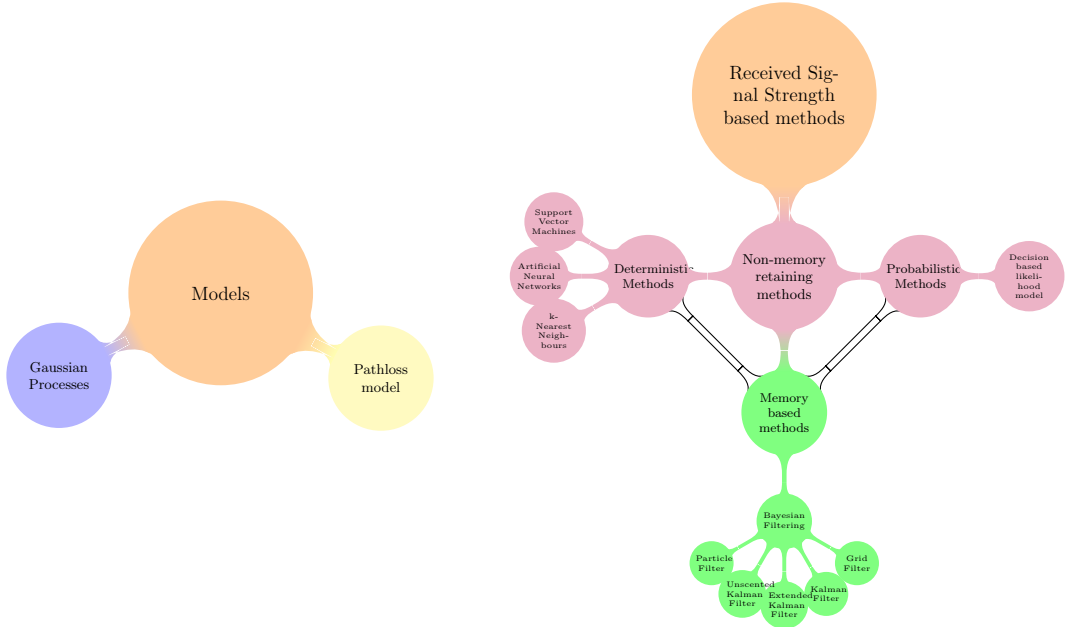


Figure 1: (left) Gaussian Processes and Pathloss models used in the thesis. (right) RSSI based methods used in the thesis. The colorless edges denote that memory based methods can be used in conjunction with non-memory based methods.

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.f). 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 November	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 and without user's presence.
- (b) Different phones.
- (c) Different orientation of phones, angles, height?

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

- (d) Different material of luminaires.(metal, plastic, metal+plastic).

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

- (e) Different orientation of BT chip (cardinal directions and upwards and downwards)
- (f) Fingerprint measuring while being still, only in 4 cardinal positions and while rotating.

2. Different calibration time for fingerprinting.
3. Different calibration points.
4. With nearest node not working.

5.2 Implementation of Methods

Next, based on the results of the experiments above implement the methods described in the 4.1.1.

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