Scene Analysis based Bluetooth Low Energy Indoor Positioning Methods

Master's Thesis Proposal

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1 Introduction

The field of indoor positioning system (IPS) came to existence due to poor performance of traditional global positioning systems (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 systems Inertial measurements units sensors, Light Emitting Diodes, Wireless Fidelity, Visual Light Communication 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.

The indoor positioning problem poses a different challenge 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 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 ActiveAhead nodes are intelligent predictive lighting solution which self-learn the pattern of movement of the users based on experience. Wirelessly mesh networked ActiveAhead 1 has a self-powered LED driver, control unit and sensor unit. The control unit enables the BLE mesh which aids the communication between other control units. The control unit also provides the intelligence to the ActiveAhead. We use beacons and nodes interchangeably in the rest of the document.

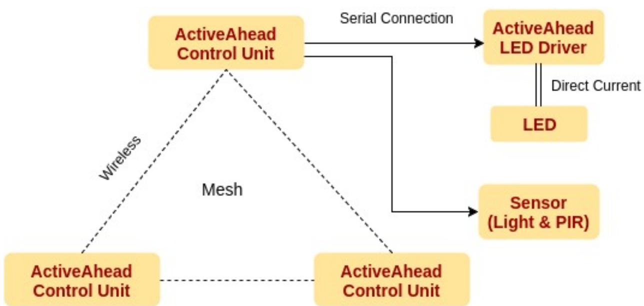

Figure 1: Wireless mesh of ActiveAhead solution.

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 BLE signals. The RSSI value which is the central component of the signal is planned to be leveraged along with sensor data from pyroelectric infrared and light sensors 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 is 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 belongs, sensor and interfaces present in vicinity, etc. Hence, this task could also be named **Self Organizing Sensor Network** [10]. 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 data using the demo android application developed in-house and test different algorithms based on hypothesis generated from the experiments in MATLAB. The outcome of the ANOLI task 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 [15]. The variety of smartphone hardwares and it's handling also exacerbates the issue of modeling. Next we discuss different algorithms used for localization.

3.1 Time of Flight based methods

Triangulation includes methods like Lateration and Angulation. Different methods include time of arrival (TOA), time difference of arrival (TDOA), Angle of Arrival (AOA) . These methods requires synchronization of one or more devices and needs estimates from at least three different known sources. These methods suffer badly due to lack of line of signal. It's not feasible to calculate the time of flight when used in conjunction with BLE, hence not used in this thesis.

3.2 RSS based methods

These are signal attenuation based models (RSS based) try to directly or indirectly learn the path loss component due to propagation because the signal in indoor setting is degraded due to multipath fading. One of the methods, Scene Analysis involves inferring about a location based on observations of the scene. This is done via features recorded for particular locations in the form of prerecorded dataset. The prerecorded dataset called reference table maps the locations with the features [17]. The reference table is then used to create a radio map, which is an interpolation from already existing points to other points in the state space. Hence, it is also called *fingerprinting* as it aims at creating unique feature map for all locations. The localization can be accomplished using Bayesian Filters (Grid Filter, Kalman Filter, Extended Kalman Filter, Unscented Kalman Filter, Sequential Monte Carlo methods like Particle Filters). 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 [17]. And, these methods are scalable when used in conjunction with GP's [17]. 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 [14]. 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 invalid, 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 [13].
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.

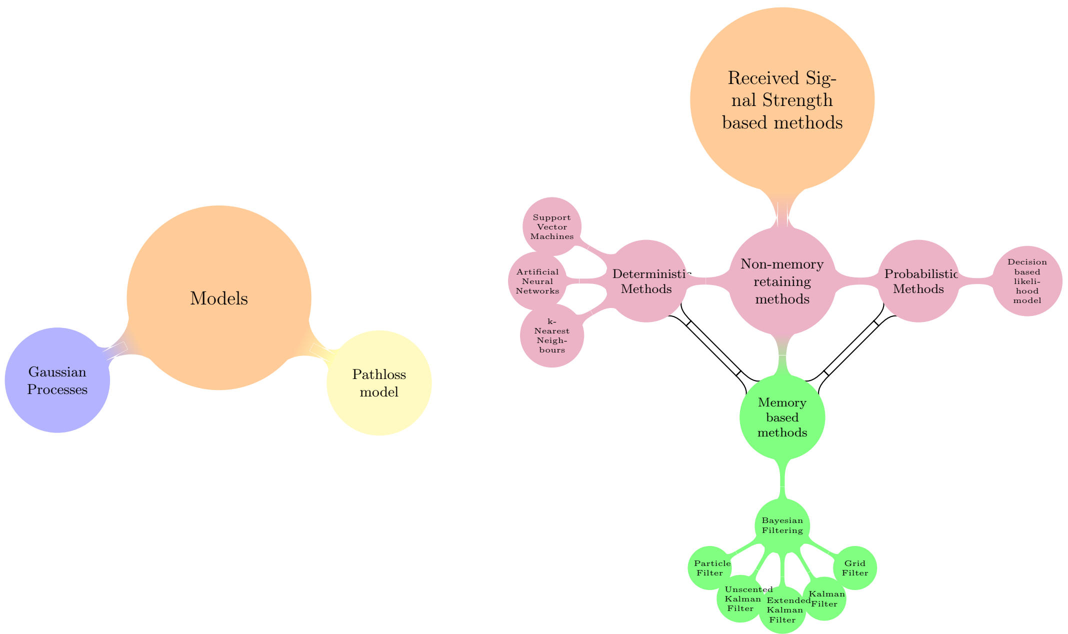

Figure 2: (left) Gaussian Processes and Pathloss models used in the thesis. (right) RSSI based methods used in the thesis. The colorless edges denote that memory based methods can be used in conjunction with non-memory based methods.

4 Methods and Materials

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.

1. **Non-memory based methods** (NMM): These methods are deterministic 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 directly estimate the position of subject 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 can make use of 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 improved posterior or state estimate.

5 Plan

The plan is to complete the ANOLI experimentation first and then move to the positioning algorithms which would use the ANOLI results. Based on the experimentation in 5 different models will be tested. The idea is to iteratively move from models to implementation of different algorithms. The measurement android application would be regularly updated to include specifications of different experiments, for example, like different calibration times, calibration points, etc. The same has been illustrated in the table 1. The different experiments required for data analysis of RSSI values are enumerated below.

1. Different Biases in RSSI measurements. Also, to analyze deviation when compared to mean from the reference data.

   (a) *User's presence*: Investigate the effect of user's presence and absence on the RSSI measurement values. Add: user shadowing application.

   (b) *Smart-phones*: Investigate how different hardwares in the smartphone affects the RSSI values. Add: Compare all the smart phones data with the radio analyzer.

   (c) *Orientation of phones*: Investigate how different angles and heights of usage of smartphones affect the RSSI measurements. Also, measuring in 4 cardinal positions and while rotating. Add: hand vs pocket

   Hypothesis: 5 dBm difference for the change in orientation [13].

   (d) *Material of the luminaires*: Investigate how different material (metal, plastic, metal+plastic) in the luminaires affects the RSSI values.

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

   (e) *Orientation of the Bluetooth module*: Investigate if the orientation of Bluetooth module has any effect on the RSSI values.

   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. Based on the results of the above experimentation, the orientation of the phone with least bias would be used to isolate this effect.

2. *Calibration time*: Investigate how different measurement times for the reference table affects the accuracy of the positioning system.

   It is the time for which we measure the RSSI values for the creating the reference database. Here, we would consider orientation with least bias to isolate this effect.

3. *Calibration points*: Investigate how different calibration points for the reference database affect the accuracy. To propose a criterion on how to select these locations.

   Select subset of points at random and run the filter 20 times and average the error. I will start with introducing the GPs and then move on to it's applications to Indoor Positioning. GPs can be used with and without the laborious finger-printing process. One of the major by-products of using GPs is that we can solve the SLAM problem and also find the unknown node location's by making them one of the

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

4. *Malfunctioning BLE chip*: Investigate how a particular algorithm would perform with one or more malfunctioning BLE chips i.e., measuring out of range RSSI values.

   The idea is to manipulate the measured RSSI values from the nearest node and run the positioning algorithm. Based on the results we would then increase the number of malfunctioning nodes.

5. *Skewness as function of distance*: Investigate how skewed the distribution of signal strength values get as the distance increases.

   At a particular location in both the scenarios, get the signal strength values for a extended period of time and plot the average rssi vs skewness. figure 7 and 8.

6. *Number of beacons vs Accuracy vs Number of calibration points*: Investigate how the number of beacons could effect the accuracy of the positioning algorithm and how

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