# A Survey on Gaussian Processes for Indoor Positioning

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**Abstract**

Gaussian processes are advanced probabilistic methods which are used to draw inference in the function space. In the field of indoor positioning, GPs have widely not only to form a appropriate likelihood model (using GP regression) but also mitigate other problems like non-line of sight (using GP classification). In this paper, we summarize the GP modeling for the indoor positioning applications.

**Keywords:** Particle Filter, Sequential Monte Carlo, Effective Sample Size, Pareto Smoothed Importance Sampling.

## 1 Introduction

location based services, location-aware services,

In this paper, we look into only RSS based positioning systems as they are widely studied mainly due to their cheap economical cost

For over two decades now Gaussian processes (GPs) have been extensively studied. The need for indoor positioning (IP) arose because the traditional Global Positioning System (GPS) faring badly indoors due to signals attenuation and scattering caused by roofs and walls. This leads to higher uncertainty in estimation of location which sometimes spans across multiple rooms sabotaging the whole positioning problem. IP has been solved using the triangulation techniques like lateration with time of arrival (TOA), time difference of arrival (TDOA), received signal strength (RSS) based or fingerprinting based scene analysis methods like decision based probabilistic method, k-Nearest Neighbour (k-NN), artificial neural networks (ANN) or proximity based methods [?] and Gaussian processes with latent variable models [?].

In this project, we estimate the physical location [?] i.e., getting the scaled 2D coordinates of the floor map. The approach used is first getting the radiomap via the fingerprinting method. Particle filter in coordination with the Gaussian process and k-NN measurement model have been used. The *augmented coordinated turn (ACT)* [?] state space model was used for modeling the physical characteristics of the system.

The use of signal strength based methods have gained attention among the research community for estimating the location of either a smart phone device or a robot [?]. Due to multipath and fading leading to unpredictable signal strength values, getting a reliable data model is an arduous task. Gaussian processes[1] provides a good back door solution for such a problem because of it's non-parametric nature.

The remainder of the paper is organized as follows. We first present the motivation for using the GPs. We then present related studies in section 2 to get a broader overview of the IP field. Then we show the modeling with detailed mathematical derivations. Next, different methodology used, followed by results and discussions. We conclude this monograph with future work.

## 2 Background

### 2.1 Indoor Positioning

The smart-phone has become the hub for all the sensors and that calls for effective usage for better localization [6].

[1] to be precise we use Gaussian process regression

GPs using BLE, WiFi, cellular network, magnetic field

The Wireless Access Points (WAPs) advertise the packets indicating its present at certain interval. The signal strength based approaches can be categorized into two. The *Range-based* approach [1] is a parametric method where the RSSI is used to estimate the distance between the receiver and all the heard WAPs. The RSSI is converted to a distance measure which is in-turn used for the localizing the receiver. The prior information in the form of location of the all the WAPs is requisite for using this methodology. On the other hand, the *Range-free* approach finds a spatial mapping of the signal strength values. Many algorithms have been proposed to solve the indoor positioning problem

Highlight the flaws of other methods to motivate the use of GPs.

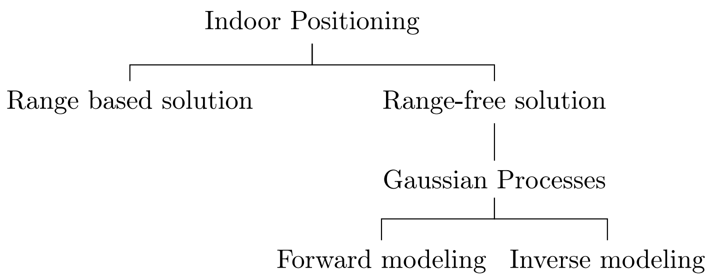


Figure 1:

### 2.2 Gaussian Processes

Gaussian processes are non-parametric methods which form the range-free methods. These are suitable for approximating non-linear function like indoor radio signals.

#### 2.2.1 Theoretical background

[7]

Schwaighofer et al. [10] were first to utilize the Gaussian process (GP) to cellular network and later Ferris et al. [4] introduced them to WLAN-based indoor localization.

**Maximizing the likelihood and its downside**

In this method, we have the GP radio-map for every beacon and then we maximize the joint likelihood of measurement from the particular beacons with respect the positions to estimate the unknown location [4]. This methodology might lead to over-confident likelihood estimates and needs a remedy in the form of smoothing operation [4]. Another smoothing could be in the form of using prior information, for example, like dynamic model. This motivates us to use the Bayesian filters [**?**]. To extend the work, Ferris et al. [4] used *Particle Filters* (PF) over mixed graphs to identify the change in the floor as well.

## 3 Advantages of GPs in Indoor Positioning

There are various properties of GP's which fit modeling signal strength based problems. Few of the important properties are given below [4].

1. *Continuous Locations*: Traditionally, GPs were known as *kriging*, which is an regression task, hence they can predict the signal strength values (with the uncertainty estimates). GPs have excellent capabilities of interpolating over other test locations. They are flexible as they don't need any designated training points for accomplishing this task.

2. *Arbitrary likelihood models*: A wide variety of complex data models can be approximated given the non-parametric nature of GPs: multiple kernels could be used in conjunction with each other [8]. Hence, GPs are can model highly non-linear signals such as RSSI [1]

3. *Correct uncertainty handling*: As the GPs come with a Bayesian flavor, along with the mean estimates they also spit out the uncertainty estimates for each value in the state space. This is mainly dependent on amount of data and the estimated noise around the test points [3].

   faragher_2013 check out the hl parts.

4. *Consistent parameter estimation*: The model selection problem in GPs helps solving the obtaining the optimal (hyper-) parameters. This is done via the maximizing the marginal likelihood [8]. These point to spatial correlation between measurements and learn the measurement noise [4].

   [11] GP is a innovation sequence in the Kalman Filter.

# 4 GP modeling for indoor positioning

In a broader sense, the GPs could be modeled in following way:

1. *Indirect* [1] modeling: A widely used approach to apply GP for positioning is through the following the equation:

$$s_j = f(x) + \epsilon \tag{1}$$

   where $s_j$ is the value of RSSI at the location $x$ for $j$-th access point. Hence, the GPs could be modeled inversely from metric space to signal space.

$$\begin{aligned} GP :& \mathbf{R}^d \rightarrow \mathbf{R} \\ x & \ \mapsto s \end{aligned} \tag{2}$$

   This might look unremarkable but works for most of the problems and could be directly applied from the filtering point of view. It enables us to model the signal strengths as *latent variables* and learn its characteristics over the position state space. The characteristics are recorded in the form *radio-maps*. Radio maps are discussed in section 5. GP here could be exploited in the form of measurement model using the learnt radio maps, as in [4].

   With the ease comes along few limitations, like the quality and amount of the fingerprint data for constructing the radio map, which is a laborious task. This approach has been called *Forward* [10] modeling by Schwaighofer et al is quite misleading.

2. *Direct* [1] modeling: Logically, it would be suitable if we could get the location estimate directly from the RSSI values i.e., from signal space to metric space

$$x = f(\mathbf{s}) + \epsilon \tag{3}$$

   where $\mathbf{s} = s_{1:j}$ is an array of RSSI measurements from $j$ access points riddled with the noise $\epsilon$ at the location $x$. Hence, the GPs could be modeled directly from signal space to metric space.

$$\begin{aligned} GP :& \mathbf{R}^q \rightarrow \mathbf{R}^d \\ \mathbf{s} & \ \mapsto x \end{aligned} \tag{4}$$

   This could be achieved through *Maximum Likelihood estimation (MLE)*, which is entrenched by type and convexity of likelihood function, and its initialization. It is not uncommon fact that MLE innately suffers from over-fitting [2]. This approach has been called *Inverse* [10] modeling by Schwaighofer et al is quite misleading. One observation from equation 3, evidently a vice, is that it assumes that the input RSSI values are noise free i.e., we tend to ignore the stochasticity of the signal propagation.

3. *Hybrid* modeling: add reference to the previous equations The *hybrid* modeling tries to overcome the limitations of *indirect* and *direct* modeling. It is an augmented form of direct model and is constructed two fold. This model overcomes the problem of initialization by intelligently using the indirect model to overcome its problem of initialization [1]. This forms the first GP fold. The second fold uses these vague location estimates and runs it through the indirect model using the MLE to get the updated location estimates. The hybrid model shows a crude mimicry of Bayesian filtering approach [9]. The first fold mimics the prediction step which is formed using the dynamic model and the second fold mimics the update step which is formed using the measurement model.

$$\begin{aligned} \tilde{x} &= f_{GP_1}(\mathbf{s}) \\ x &= g_{GP_2}(\tilde{x}) \end{aligned} \tag{5}$$

where $f$ is function which follows $GP_1$ from the equation 4 while $g$ follows $GP_2$ from the equation 2, $\tilde{x}$ is the predicted estimate of location from signal strengths $\mathbf{s}$ from luminaires whereas $x$ is the updated location estimate.

change it; for reference only.

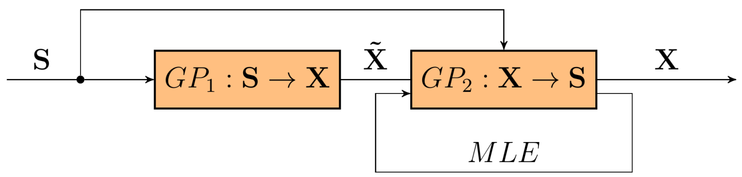


Figure 2: Hybrid model. courtesy [1].

To incorporate the stochasticity in the RSSI values, we can also model the inputs as *Noisy Input GP (NIGP)* and also include a Gaussian prior on the state [1].

$$\begin{aligned} NIGP :& \mathbf{R}^q \to \mathbf{R}^d \\ \mathbf{s} &\mapsto x \end{aligned} \tag{6}$$

### 4.1 Fingerprinting

### 4.2 SLAM

The problem of simultaneous localization and mapping (SLAM) is real time fingerprinting and positioning technique. In SLAM, you create the database of

The work of [4] paved way for *Distributed Particle Simultaneous Localization And Mapping* (DP-SLAM) [3].

## 5 Methodology used in Indoor Positioning

Categorizing the use of GP's based on fingerprinting approach, we have:

- **Fingerprinting-based**

  1. **Radiomaps**: Radiomap is a set of learnt features for a particular a access point over a region of interest. As discussed, the access point could BLE beacon, WiFi router or GSM cell tower. Deterministically, various sophisticated path loss models have been used and studied [12]. Traditionally, the GPs are used for used for generating the radio-maps [10]. Radio-maps have been called by various names, like *reference maps*, *likelihood maps* [1], *prior maps* [3] or *signature maps* [13]. Radiomaps interpolate the signal strength values to other points of interest in the state space. These maps serve as a prior knowledge in the positioning tasks. These maps are used for inferring the location of the user. [5] was the first to give the mathematical formulation and theoretical basis for radiomaps.

2. **Measurement Model Likelihood**
3. **Hybrid Methods**

- **Fingerprinting-free**
  1. **Gaussian Process Latent Variable Models (GP-LVM)**:
     This methodology is devoid of the laborious data calibration phase (fingerprinting) and directly maps the high dimensional signal strength data to low dimension spatial information. WiFi-SLAM GP-LVM is an extension of Gaussian Process Dynamical Models (cite me;Wang et al, 2006) with an addition of likelihood model for the hidden variables [4].

# 6 Performance metrics

# 7 Enabling Technologies

## 7.1

# 8 Results & Discussions

# 9 Conclusions

# References


[1] M. Aravecchia and S. Messelodi. Gaussian process for RSS-based localisation. In *2014 IEEE 10th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*, pages 654–659, October 2014.

[2] Christopher M Bishop. Pattern recognition and machine learning (information science and statistics) springer-verlag new york. *Inc. Secaucus, NJ, USA*, 2006.

[3] R Faragher and R Harle. Smartslam-an efficient smartphone indoor positioning system exploiting machine learning and opportunistic sensing. In *ION GNSS*, volume 13, pages 1–14, 2013.

[4] Brian Ferris Dirk Hähnel and Dieter Fox. Gaussian processes for signal strength-based location estimation. In *Proceeding of Robotics: Science and Systems*, 2006.

[5] Ville Honkavirta, Tommi Perala, Simo Ali-Loytty, and Robert Piché. A comparative survey of wlan location fingerprinting methods. In *Positioning, Navigation and Communication, 2009. WPNC 2009. 6th Workshop on*, pages 243–251. IEEE, 2009.

[6] Christopher Langlois, Saideep Tiku, and Sudeep Pasricha. Indoor localization with smartphones: Harnessing the sensor suite in your pocket. *IEEE Consumer Electronics Magazine*, 6(4):70–80, 2017.

[7] Hyuk Lim, Lu-Chuan Kung, Jennifer C Hou, and Haiyun Luo. Zero-configuration, robust indoor localization: Theory and experimentation. Technical report, 2005.

[8] Carl Edward Rasmussen and Christopher KI Williams. *Gaussian processes for machine learning*, volume 1. MIT press Cambridge, 2006.

[9] Simo Särkkä. *Bayesian filtering and smoothing*, volume 3. Cambridge University Press, 2013.

[10] Anton Schwaighofer, Marian Grigoras, Volker Tresp, and Clemens Hoffmann. Gpps: A gaussian process positioning system for cellular networks. In *Advances in Neural Information Processing Systems*, pages 579–586, 2004.

[11] Robert H Shumway and David S Stoffer. *Time series analysis and its applications: with R examples*. Springer Science & Business Media, 2006.

[12] José Vallet, Ossi Kaltiokallio, Jari Saarinen, Matthieu Myrsky, and Maurizio Bocca. On the sensitivity of rss based localization using the log-normal model: An empirical study. In *Positioning Navigation and Communication (WPNC), 2013 10th Workshop on*, pages 1–6. IEEE, 2013.

[13] Simon Yiu, Marzieh Dashti, Holger Claussen, and Fernando Perez-Cruz. Wireless rssi fingerprinting localization. *Signal Processing*, 131:235–244, 2017.