A Comparison of k-NN and Gaussian Process Measurement Model for Fingerprinting based Indoor Positioning

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Outline

Why indoor positioning?

Setup and Methodology

- A test site was selected, and beacons[4] were installed. The reference measurements were taken at pre-selected locations. The measurements are the received signal strength indication (RSSI) values of the beacons.

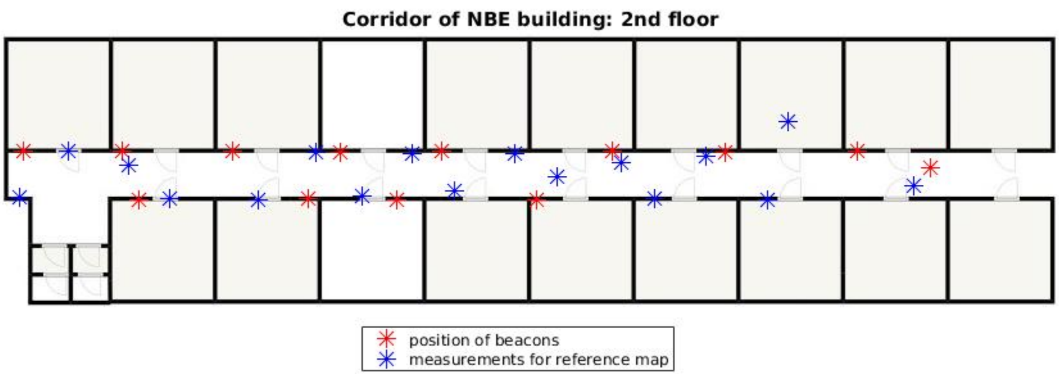

Figure 1: The floor-plan with positions of the beacons and locations of reference measurements.

Setup and Methodology I

- Bootstrap PSIS Particle Filter with measurement models
  1. using Gaussian Process (requires predictions using GP regression: used constant, as RSSI values are far from zero, and squared exponential covariance function)
  2. using k-Nearest Neighbour measurement model. (requires just the reference table, no radio-map required)

Setup and Methodology II

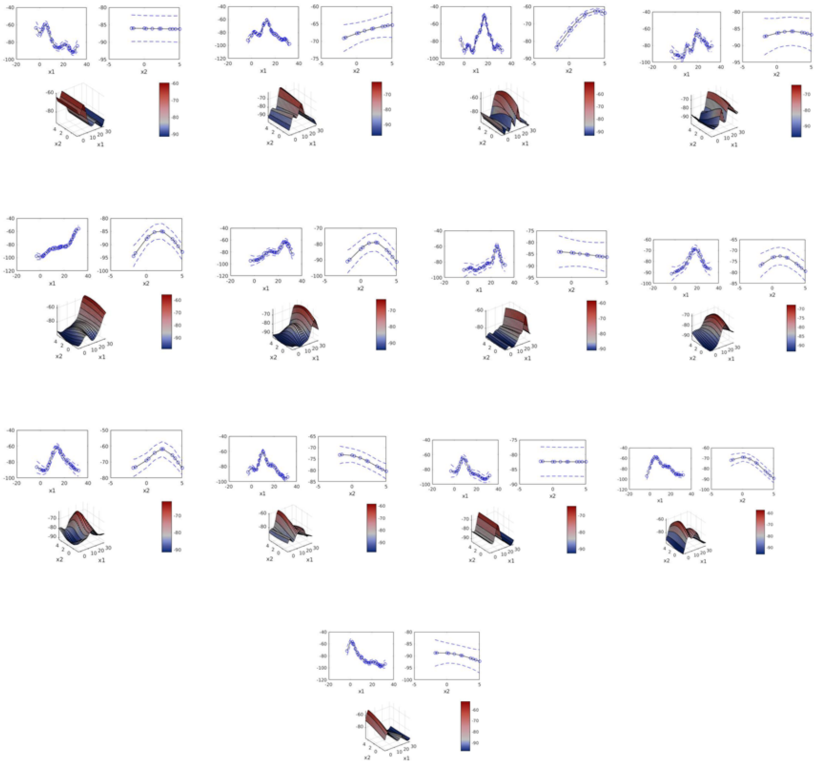

Figure 2: The predictions using simple GP regression.

Particle Filter

- Particle Filter is a Sequential Monte Carlo method.
- In this project, we have used Pareto Smoothed Importance Sampling Particle Filter(PSIS-PF). It is novel method developed at the Probabilistic Machine Learning group, results yet to be published.

PSIS Particle Filter

PSIS Particle Filter (without smoothed weights)

- Draw point $x_k^{(i)}$ from the importance distribution:

$$x_k^{(i)} \sim \pi(x_k | x_{k-1}^{(i)}), \qquad i = 1, ..., N$$

- Calculate the new weights and normalize them:

$$w_k^{(i)} \propto w_{k-1}^{(i)} \frac{p(y_k | x_k^{(i)}) p(x_k^{(i)} | x_{k-1}^{(i)})}{\pi(x_k^{(i)} | x_{0:k-1}^{(i)}, y_{1:k})}, \qquad i = 1, ..., N$$

- Get the Pareto shape parameter $\hat{\mathrm{k}}$ from the weights distribution and if $\hat{\mathrm{k}}$ is greater than 0.7 (or 1), perform resampling.

PSIS Particle Filter

- Dynamic model: In this project, we are using classic bearing only tracking(BOT) model with four states i.e., location(x, y) and velocity$(\dot{x}, \dot{y})$.

$$\begin{pmatrix} x_t \\ y_t \\ \dot{x}_t \\ \dot{y}_t \end{pmatrix} = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{pmatrix} x_{t-1} \\ y_{t-1} \\ \dot{x}_{t-1} \\ \dot{y}_{t-1} \end{pmatrix} + q_{t-1}$$

PSIS Particle Filter

- Measurement model:
  1. GP: At each step, we perform a GP prediction on all the particles and get the likelihood value when compared to the measurement value.
  2. k-NN:
     1. Create an initial weight (not same as PF weights) estimate, by taking the inverse of square of euclidean distance of measurements and reference value for each beacon. So, here the one with least distance(or similar RSSI values will have maximum weight) and sort the reference locations based on these weights.
     2. Get the inverse of euclidean distance kernel between particles and sorted reference locations.
     3. Now, sweep through the weights (dimension of reference locations) through the kernel matrix, and sum all the values over the beacons.

Simulation Time!

Results(not validated)

- For the GP measurement model, on the maximum deviation is approximately is 3 meters.
- For the k-NN measurement model, it is 9 meters.

Challenges Faced

Fitting a Gaussian Processes

- Getting the right priors, in case you have less data.
- Optimization of the parameters.

Where to go next...

- Because, GP's can have weird predictions at the boundaries, we can use a mean function (path loss model).
- Can add extra monotonicity boundary conditions.
- Problems with constant covariance functions.
- Use the Augmented Coordinated turn dynamic model, for tracking the human motion more accurately.

Thank you for your attention!

Reference

- 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
- 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
- B. Ferris, D. Fox, and N. Lawrence. WiFi SLAM Using Gaussian Process Latent Variable Model. In JCAI, January 2007.
- Beacon, link: https://store.kontakt.io/our-products/30-double-battery-beacon.html.