Live Demo Available

Wi-Fi Indoor Localization

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Introduction

For indoor localization, GPS is inadequate due to multi-path propagation and signal attenuation. A practical solution is using the Wi-Fi signals that ubiquitously blanket almost all working areas. This will perform Bayesian filtering to estimate location from signal strength measurements.

Gaussian Process

We use Gaussian Proecss to generate an observation model for signal strength measurement from calibrated data.
A distribution can be derived with mean μ_{x_*} and variance $\sigma^2_{x_*}$ as

$$f_{x_*}|X, y, x_* \sim \mathcal{N}(\mu_{x_*}, \sigma^2_{x_*})$$

$$\text{with } \mu_{x_*} = k_*^T(K + \sigma_n^2)^{-1}y \quad (1)$$

$$\sigma^2_{x_*} = k(x_*, x_*) - k_*^T(K + \sigma_n^2)^{-1}k_* \quad (2)$$

where y is the training observations, σ_n is observation noise, k_* is the covariances between input x_* and traning inputs X, $k(x_*, x_*)$ and K are the covariance matrix of x_* and X respectively. Computing the covariance matrix by the kernel

$$k(x_p, x_q) = \sigma_f^2 \exp(-\frac{1}{2l^2}|x_p - x_q|^2)$$

Here, σ_f^2 is the signal variance and l is length scale.

Experimental Testbed

Our experimental testbed is located at level 5 of Ingkarni Wardli building. The layout of the floor is shown in Figure 1.

Figure 1. Map of the floor where the experiments were conducted. The red circles denote locations where signal strength measurements were collected.

Signal Strength Modelling

In the context of Wi-Fi localization, the inputs X correspond to locations and the observations y correspond to signal strength measurements collected at these locations. During localization, the signal strength measurement can be cnomputed at any locations by (1) and (2).

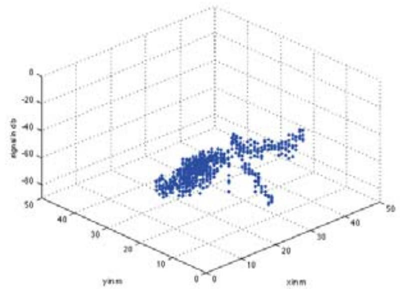

Figure 2. Raw signal strength measurement for one access point

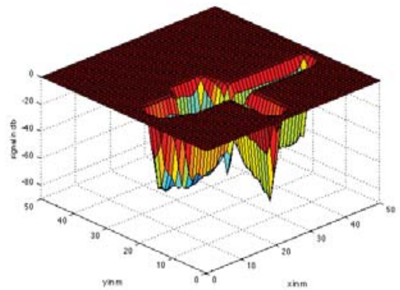

Figure 3. Mean of GP prediction for one access point

Figure 2 illustrates the raw signal strength measurement for one access point on our experimental testbed. The mean of GP prediction for these data points are shown in Figure 3. As can be seen, the GP smoothly approximates these data points.

Unscented Kalman Filter

Since our observation model generated by GP is non-linear, we implement Bayesian filtering using UKF that can solve non-linear system. UKF representing the distribution using a set of carefully chosen sample points. These sample points can capture the mean and variance of the distribution. Then these sample points are propagated through the non-linear system, to capture the mean and variance of posterior distribution. To do this, a method called unscented transform is used.

Unscented Transform

Consider propagating a random variable x through a non-linear function $y = f(x)$. Assuming x has mean $\bar{x}$ and variance $\mathcal{P}_x$. Let X be a set of $2L+1$ (L is dimension of x) *sigma* vector X_i given by

$$X_0 = \bar{x}$$

$$X_i = \bar{x} + (\sqrt{(L+\lambda)\mathcal{P}_x})_i \quad i = 1, \ldots, L$$

$$X_i = \bar{x} - (\sqrt{(L+\lambda)\mathcal{P}_x})_{i-L} \quad i = L+1, \ldots, 2L$$

where $\lambda = \alpha^2(L+k) - L$ is a scaling parameter. The constant α controls the spread of the sampled points around $\bar{x}$. The constant k is a second scaling parameter, $(\sqrt{(L+\lambda)\mathcal{P}_x})_i$ is the ith column of matrix square root. Then, these sampled points are propagated through the non-linear function,

$$Y_i = f(X_i) \quad i = 0, \ldots, 2L$$

and the mean and variance for the non-linear function y are approximated by the weighted mean and variance of the sampled points,

$$\bar{y} \approx \sum_{i=0}^{2L} \mathcal{W}_i^{(m)} Y_i$$

$$\mathcal{P}_y \approx \sum_{i=0}^{2L} \mathcal{W}_i^{(c)} [Y_i - \bar{y}][Y_i - \bar{y}]^T$$

where the weights $\mathcal{W}_i$ is given by

$$\mathcal{W}_0^{(m)} = \lambda/(L+\lambda)$$

$$\mathcal{W}_0^{(c)} = \lambda/(L+\lambda) + (1 - \alpha^2 + \beta)$$

$$\mathcal{W}_i^{(m)} = \mathcal{W}_i^{(c)} = 1/(2L+\lambda) \quad i = 1, \ldots, 2L.$$

where β is used to incorporate prior knowledge of the distribution of x.

Experimental Result

Figure 4. Tracking on the corridors

Assuming the tetsting data were collected by a constant velocity model, Figure 4. illustrates the offline tracking result on one path using UKF. The red circles denote the ground truth locations and the blue crosses denote the UKF predictions.

Conclusion

We presented GP and UKF for localization based on signal strength measurement. We developed a tracking application on an android tablet, and our experiments show that the application can accurately track a person moving through a indoor environment.

Regference

[1] B. Ferris, D. Hahnel and D. Fox. Gaussian Processes for Signal Strength-Based Location Estimation. *In Proc. of Robotics Science and Systems*, 2006.

[2] C.E. Rasmussen and C.K.I. Williams. Gaussian Processes for Machine Learning. *The MIT Press*, 2006.

[3] Wan, E. A., and van der Merwe, R. The Unscented Kalman Filter for Nonlinear Estimation. *In Proc. of IEEE Symposium 2000 (AS-SPCC)*, 2000.