Brief Report

WiFi Localization Method Using a Gaussian Process Particle Filter

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1. Introduction

Indoor localization with low-cost sensors remains an open problem. At the same time, accurate knowledge about the position of a user offers the opportunity for a variety of novel services in many environments in which GPS is not available.

A large number of studies have been conducted on wireless-based localization for GPS-denied environments. These methods use global systems for mobile communication (GSM), ultra wideband (UWB), worldwide interoperability for microwave access (WiMAX), Bluetooth, RFID, or WiFi.(1,2) Among these systems, WiFi is one of the most useful wireless signals for indoor global localization. WiFi antennas are available in almost all devices, and access points that are already present in the environment can be readily used. Furthermore, WiFi-based localization is resilient to ambiguities due to the unique identifier provided by the access points.

The main problem in WiFi-based localization is the construction of accurate signal models. In real environments, signals are subject to reflections, diffractions, refractions, and other jamming factors. Therefore, estimating an accurate model of a sensor signal is very difficult. Another problem is that the density of preliminarily training data of WiFi affects localization accuracy.

In the present paper, we address WiFi-based localization problems using the Gaussian process and a Gaussian process particle filter. Gaussian process regression takes into account the presence of training data and estimates the uncertainty of models. In addition, the Gaussian process particle filter automatically increases its uncertainty when the target enters an area in which there are insufficient training data.

2. Gaussian Process for the Wireless Signal Model

The Gaussian process (GP) (3) learns regression functions based on training data. **Figure 1** shows an example of a signal model represented by a GP. In Fig. 1, the solid red line shows the mean signal model represented by the GP. The GP also learns the variance of the model, as shown by the dashed blue line. Note that the uncertainty of the model increases or decreases according to the presence of training data. For example, the uncertainty of the model is low if there are numerous training data around the x-interval [1, 3], whereas the uncertainty of the model is high if there are no training data around the x-interval [4, 7]. The GP has several advantages for wireless signal modeling:

• Uncertainty estimation: As indicated above, in contrast with other regression methods, the GP can estimate uncertainty models. This enables localization to handle the importance of each sensor model. If a target enters an area in which insufficient training

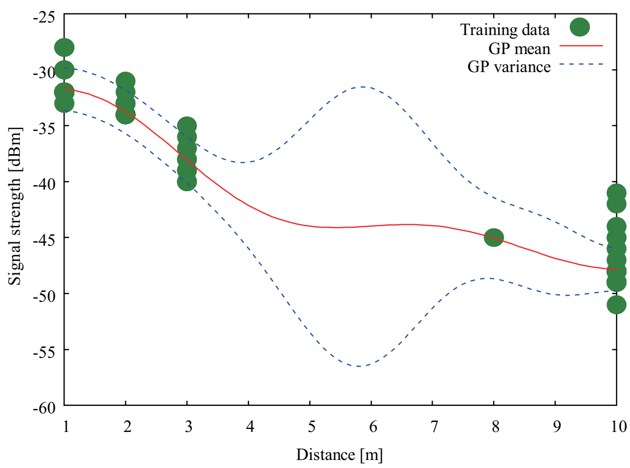


Fig. 1 The model of WiFi signal strength represented by GP regression.

data exist, the importance of a model for localization automatically decreases. In contrast, if a target enters an area in which sufficient training data exist, the importance increases.

• Model flexibility: The GP does not depend on the availability of parametric models. The models are learned from training data using non-parametric regression. If a parametric model is available, the GP can integrate the parametric model.

• Continuous model: The GP expresses a continuous sensor model with a kernel function, hyperparameters, and training data. Even though there is insufficient training data, a target can estimates its position with increasing uncertainty.

3. Gaussian Process Particle Filter for WiFi Localization

We use the particle filter [4] together with WiFi signal models based on the GP. The proposed method is based on the Gaussian process particle filter (GP-PF).[5] We applied the GP-PF to the WiFi localization problem. The GP-PF recursively estimates the posterior of a robot's pose as follows:

$$p(x_t \mid z_{1:t}, u_{0:t-1}) \propto p(z_t \,||\, x_t)\int_{\hat{x}}(x_t \mid \hat{x}, u_{t-1})p(\hat{x} \mid z_{1:t-1}, u_{0:t-2})d\hat{x}, \quad (1)$$

where $u_{0:t-1}$ is the motion command executed by the robot, and $z_{1:t}$ are observations. The motion model $p(x_t \mid \hat{x}, u_{t-1})$ denotes the probability of the robot's state x_t given that the robot executes u_{t-1} in the state $\hat{x}$. The observation model $p(z_t \mid x_t)$ denotes the likelihood of the observation. The GP-PF approximates the belief of the robot with a set of hypotheses referred to as particles and updates the belief iteratively by sampling these particles from the motion model. Then, the GP-PF computes a weight w according to the observation model, as follows:

$$w = \prod_{j=1}^{n} \overline{w}_j \qquad (j = 1, \ldots, n) \quad , \qquad (2)$$

where n is the number of currently observed access points, and $\overline{w}$ is the importance weight of the signal of each access point given by

$$\overline{w}_j = p(ss_j; \mu_{gp}(x, D_j), \Sigma_{gp}(x, D_j)) \quad , \qquad (3)$$

where

$$p(ss_j; \mu_{gp}, \Sigma_{gp}) = \frac{1}{(2\pi)^{\frac{k}{2}} \mid \Sigma_{gp} \mid^{\frac{1}{2}}} e^{-\frac{1}{2}(ss_j - \mu_{gp})\Sigma_{gp}{}^{-1}(ss_j - \mu_{gp})} \quad , \qquad (4)$$

where $p(ss_j; \mu_{gp}, \Sigma_{gp})$ is the probability density of the received signal strength ss_j, expressed in terms of the mean $\mu_{gp}(x, D_j)$ and the covariance $\Sigma_{gp}(x, D_j)$ of the GP. The term D_j is the training data of WiFi signals, and k is the number of dimensions. Particles are resampled according to weight w. **Figure 2** shows an example of the GP-PF in an indoor environment. In this environment, we used signals of existing access points and did not assign additional access points. However, the GP-PF could localize the target uniquely almost everywhere in the building with high accuracy.

4. Conclusion

We have introduced a GP for WiFi sensor signal models. The GP can accurately approximate a signal strength model of sensors based on training data and can estimate the uncertainty model, which improves localization accuracy. The GP-PF integrates GP motion prediction and observation models into a particle filter and also incorporates the advantages of the GP.

References

(1) Bahl, P. et al., "RADAR: An In-building RF-based User Location and Tracking System", *Proc. of the IEEE Int. Conf. on INFOCOM* (2000), pp. 775-784.

(2) LaMarca, A. et al., "Place Lab: Device Positioning Using Radio Beacons in the Wild", *Proc. of the 3rd Int. Conf. on Pervasive Computing*, Vol. 3468 (2005), pp. 116-133.

(3) Rasmussen, C. E. et al., *Gaussian Processes for Machine Learning* (2006), The MIT Press.

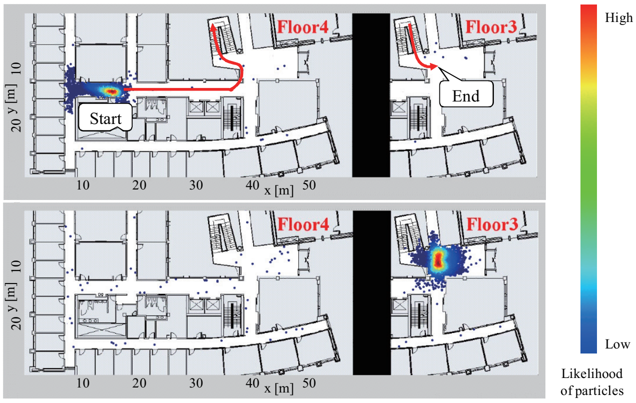
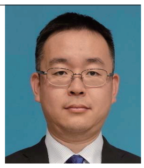


Fig. 2 Localization results of particles at the start point (upper) and the end point (lower). The red line indicates the rough pathway of the target.

(4) Frank, D. et al., “Monte Carlo localization for mobile robots”, *Proc. of the IEEE Int. Conf. on Robotics and Automation*, Vol. 2 (1999), pp. 1322-1328.
(5) Ko, J. et al., “GP-BayesFilters: Bayesian Filtering Using Gaussian Process Prediction and Observation Models”, *Autonomous Robots Journal*, Vol. 27, No. 1 (2009), pp. 75-90.



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