Poster Abstract: EcoLoc: Encounter-Based Collaborative Indoor Localization

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Abstract

This works presents a collaborative indoor localization system which provides a lightweight location estimation solution for resource constrained IoT devices. The proposed EcoLoc, an encounter-based collaborative indoor localization system, uses the chance of encounter to enable the sharing and composition of multiple trajectories which are generated by Pedestrian Dead Reckoning. A collaborative version of Conditional Random Field is developed to merge these trajectories and generate the most probable location while significantly shortening the convergence distance compared to the state-of-the-art techniques as particle filter. EcoLoc runs in real-time and can be distributed to resource-limited devices as opposed to running on centralized servers. Using the Android tablet and Broadcom WICED Sense IoT platform, the convergence distance can be shorten by up to 40% on Android tablet and up to 50% on the WICED-Sense.

1 Introduction

The knowledge of location is fundamental to enabling devices in the Internet of Things (IoT) to behave in an intelligent way. While outdoor localization is relatively well understood, indoor localization remains a challenge especially for many IoT devices [7, 11]. Existing indoor localization techniques can be categorized into reference-based vs. self-referential respectively [13]. Our indoor localization system is developed based on self-referential technique.

Self-referential localization techniques, which are also generally called dead reckoning, measure the device's own displacement relative to its initial position to determine its current location. In our work, we consider inertial sensors to estimate the moving distance. The inertial sensors we used have been miniaturized and are found in many mobile devices and sensor tags. One advantage is that all sensors are small, low-power, inexpensive, and self-contained to track the trajectory independent of landmarks. The common mathematical techniques mainly used in the computation part include the Kalman Filter (KF) [2,3,9], Hidden Markov Models (HMMs) [6,8], and Particle Filters (PF) [5,10]. However, these models tend to be computationally intensive for many wearable IoT devices such as the WICED Sense.

To provide an applicable solution enabling location sensing universally by all mobile IoT devices, this work present a lightweight indoor localization system which utilizes the inertial sensors and collects the trajectoires from other users by exploiting the encounter opportunities. Upon encounter, our system exchange trajectories between two users to enable fast detection of respective locations on the map, without relying on centralized servers and even in the absence of beacons or landmarks.

2 EcoLoc: Encounter-Based Collaborative Indoor Localization

EcoLoc utilizes Conditional Random Field (CRF) to manage the trajectories, which are generated from pedestrian dead reckoning and obtained from other users upon encounter, and proposes a real-time tracking algorithm to estimate the user location. CRF can be represented by various feature functions accompanied by weight λ_i formulated as:

$$p(\vec{S}|\vec{Z}) \propto \prod_{j=1}^{n} \exp\left(\sum_{i=1}^{m}(\lambda_i f_i(s_{j-1}, s_j, \vec{Z}, j)\right) \tag{1}$$

where j denotes the position in the observation sequence and m is the number of feature functions.The feature functions f_i represent the constraints provided by the collected observations such as floor map or trajectory.

In EcoLoc, CRF consists of feature functions that describe the possibility of location transition by using the corresponding observation [12]. The step detection decides if the CRF estimation is enabled. The heading orientation is used as observation, Z_t^θ, to define our feature function. We assume the heading orientation is a log-normally distributed random variable so that probability density of the log-normal distribution is leveraged to formulate our feature function as follows:

$$f_1 = \ln\left(\frac{1}{\sqrt{2\pi\sigma_\theta^2}}\right) - \frac{(Z_t^\theta - \theta(S_{t-1}, S_t))^2}{2\sigma_\theta^2} \tag{2}$$

where σ_θ^2 is the heading variance of observations Z_t^θ and $\theta(S_{t-1}, S_t)$ is the heading orientation between the last state S_{t-1} and the state S_t that we estimate for the current step. Our CCRF is illustrated in Fig. 1. It extends the current trajectory with the acquired trajectory from the encounter events. Suppose the length of the acquired trajectory is k steps and our trajectory is t steps, the merged trajectory may not be used to estimate the current location since the estimated location is at step $(t+k)$ instead of at step t. Therefore, CCRF reverses the acquired trajectory and estimate the location at step $(t+2k)$.

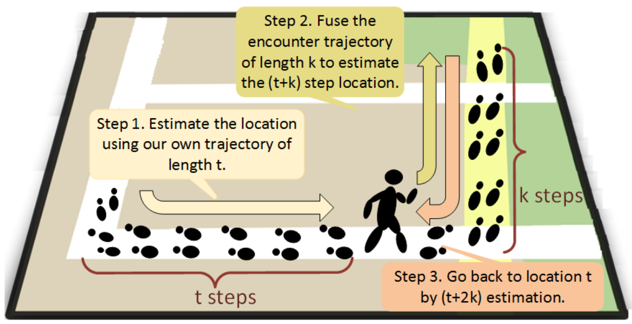

Figure 1: Collaborative Conditional Random Fields

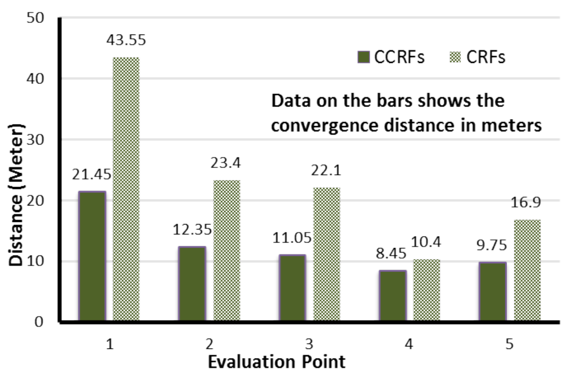

Figure 2: The Comparison of Convergence Distance for WICED-Sense among Five Evaluation Points

The CCRF can be formulated as follows:

$$p(\vec{S}|\vec{Z}) \propto \prod_{j=1}^{t+2k} \exp\Big(\sum_{i=1}^{m}(\lambda_i f_i(s_{j-1}, s_j, \vec{Z}, j))\Big) \tag{3}$$

At every step, each state will get the probability of walking to it from other possible states. Therefore, we develop a real-time algorithm to track the most probable state and geneate the possible location.

3 Evaluation

A short *convergence distance* means EcoLoc can operate either without beacons or can operate well while requiring much lower density of deployed beacons. Fig. 2 shows the convergence distance is significantly shortened by up to 50% compared to the non-encounter CRF using WICED-Sense tags. The experimental results on the tablet are shown in Fig. 3. Both CRF and CCRF have shorter convergence distances than PF and CPF do. This is because CRF captures the constraints and is able to provide the most probable location immediately based on the prebuilt states. In summary, the encounter mechanism significantly help CRF-based localization to reduce the convergence distance.

4 Conclusions

We propose EcoLoc, which exploits sharing of trajectories between devices upon encounter as a way to estimate the location on the map while requiring up to 50% shorter convergence distance than previous techniques. In addition, the

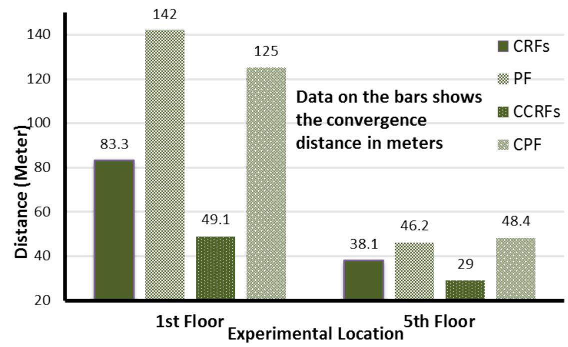

Figure 3: The Comparison of Average Convergence Distance for Tablet on 1st and 5th Floor

computation effort is also reduced significantly, thanks to the use of our CCRF model. The use of BLE makes it practical because it uses the existing RF interface for not only communication but also proximity sensing and encounter exchange.

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