Poster Abstract: EcoLoc: Encounter-Based Collaborative Indoor Localization

Hsin Chung Chen†‡, Yi Lin Chen†‡, Chia Hsun Wu‡, Mohammad Abdullah Al Faruque†‡, Pai H. Chou†‡

†Department of Electrical Engineering and Computer Science, University of California, Irvine, CA, USA
‡Department of Computer Science, National Tsing Hua University, Hsinchu, Taiwan

{hsinchuc, alfaruqu, phchou}@uci.edu, {lin781219, k8142311}@gmail.com

Abstract
This work 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 reducing 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 shortened 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 presents a lightweight indoor localization system which utilizes the inertial sensors and collects the trajectories 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 $\lambda_i$ formulated as:

$$p(\tilde{S}|\tilde{Z}) \propto \prod_{j=1}^{n} \exp \left( \sum_{i=1}^{m} (\lambda_{fi}(s_{j-1}, s_j, \tilde{Z}, j)) \right)$$

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, $Z^\theta$, 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:

$$f_i = \ln \left( \frac{1}{\sqrt{2\pi\sigma^2_\theta}} \right) - \frac{(Z^\theta - \theta(S_t-1, S_t))^2}{2\sigma^2_\theta}$$

where $\sigma^2_\theta$ is the heading variance of observations $Z^\theta$ 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 $(t+2k)$. 
The CCRF can be formulated as follows:

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

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 generate 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 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.

5 References