Localization Accuracy of Crowd Sourcing based Indoor Localization

1. Related work

The inability to use GPS indoors has led to myriad approaches based on alternative signals, ranging from infrared to acoustic and visual. There have also been localization systems based on a deployment of RF transmitters and sniffers or RFID.

While each of these approaches offers certain advantages (e.g., high accuracy in the case of acoustic ranging), the need for special purpose hardware and infrastructure is a significant challenge.

2. RF Fingerprinting based Localization

Radio Frequency (RF) fingerprinting, based on WiFi or cellular signals, has been a popular approach to indoor localization. the inertial sensors (e.g., accelerometer, compass ,gyroscope) present in the mobile devices such as smartphones carried by users, to track them as they traverse an indoor environment, while simultaneously performing WiFi scans.

Localization based on measuring the RF signal of a wireless LAN has the significant cost advantage of leveraging an existing infrastructure.

3. Modeling instead of Calibration Modeling Steps

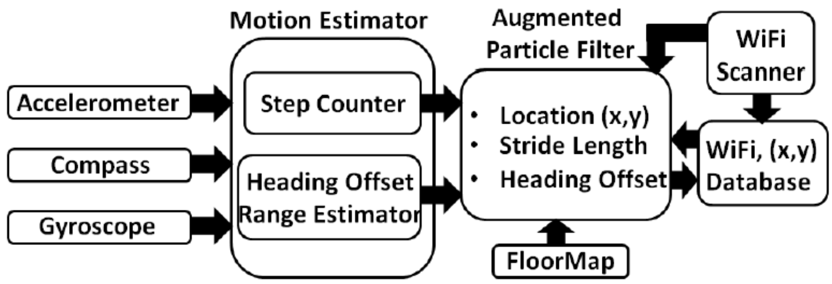

Figure3.1 the whole structure picture

There are two key components: Placement Independent Motion Estimator (PIME) and Augmented Particle Filter (APF).

PIME uses mobile sensors such as the accelerometer, compass, and gyroscope to estimate the user’s motion.

The APF uses the motion estimates from PIME and the floor map as input to track the user’s location on the floor.

The key function of the APF is to track the probability distribution of a user’s location as he/she walks on the floor.

WiFi database comprises WiFi measurement annotated with location information.

After the WiFi database has been initialized using the data from the first user, for subsequent users, APF uses information from WiFi scans and the current WiFi database, to obtain a confined initial location distribution。

The training data obtained from each subsequent walk is in turn used to refine the existing WiFi database, thus making it more accurate for the next walk.

4. Counting steps

Most men carry their phones in front pant pockets, some carry in their shirt pockets or rear pant pockets

Women most often carry them in their hands or in handbags and sometimes in pant pockets.

Figure 4.1 depicts the acceleration values seen along the three axes by a mobile phone carried by two different users, one carrying it in his shirt pocket and the other in his front pant pocket.

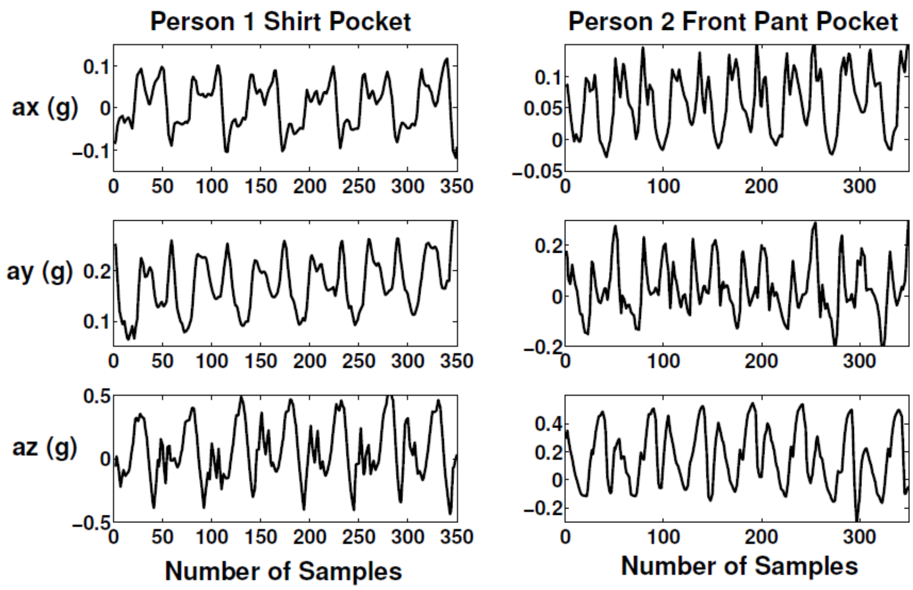

Figure 4.1 A mobile carried by different users

5. Performance of step counting

	Hand While Using	Pant Front Pocket	Pant Back Pocket	Hand Not Using	Shirt Pocket	Hand bag	Over (all)
False +ive	0%	0%	0%	0%	0%	0%	0%
False -ive	2%	0%	0%	0%	0%	0%	0.6%
True +ive	100%	100%	100%	100%	100%	100%	100%
True -ive	98%	100%	100%	100%	100%	100%	99.4%

Figure5.1 The accuracy of step counting

Figure 5.1 presents the findings from our evaluation of step counting. A false positive means that an extra step was counted while the user was in idle state, while a false negative means that a step was missed while the user was walking. Table 1 shows that these error rates are very low, often zero, for various placements of the phone across users.

6. Estimating heading offset range

To track the user's path, we must estimate the user's direction of walking. However, the compass reading might not be aligned with the direction of motion of the user. We refer to this difference between the compass reading and the direction of motion of the user as the heading offset (HO). HO arises due to a combination of two factors: magnetic offset and placement offset.

7. Tracking using argument particle filter (APF)

The key idea is that as a user continues to walk in an indoor environment, navigating through hallways and turning around corners, the possibilities for the user's path and location shrink progressively.

8. Put it all together: crowdsourcing

Using existing measurement database for subsequent crowdsourcing. We can determine where in the floor a certain WiFi measurement was taken and thereby generate location-annotated WiFi measurements of the form (location, WiFi RSS). This database of measurements can then be used to locate new users using existing WiFi localization techniques. We now describe the two WiFi localization schemes used in our evaluation.

9. Horus

We can get the conclusion that the 50%ile and 80%ile errors are 1.2m and 2.3m, respectively, which are comparable to those seen when manually-gathered data is used for training (the curves labeled EZ and HORUS). This encouraging result suggests that crowdsourcing could be effective and could enable localization with high accuracy, provided the space is well-covered by users during the course of their crowdsourcing walks.

10. Reference

[1]Zee: Zero-Effort Crowdsourcing for Indoor Localization