No need to War-Drive

Unsupervised Indoor Localization

He Wang, Souvik Sen, Ahmed Elgohary, Moustafa Farid, Moustafa Youssef, Romit Roy Choudhury

The Problem Definition:

With advancements in indoor applications, the research and development in the field of indoor localization have become quite vast. Many theoretical models, simulations, and amazingly implemented systems are already set up. But no solution is perfect and there is always some room for improvement and advancement. Over time, we have read about indoor localization systems that are ultrasound-based (Bat & Cricket), RF-base, Image-based (Hocus), Wi-Fi-dependent, MIMO-based (ArrayTrack), or GPS Fixes based (EZ) but all these systems either need a lot of calibration to be done or require specific (expensive) infrastructure setup or rely on GPS or require the computation to be done on the Access Points (APs) end (as in ArrayTrack). Moreover, most of these solutions need war driving. In this paper, the author very well presents the idea of **UnLoc**, an unsupervised indoor localization solution that doesn't rely on war-driving, it doesn't depend on the infrastructure setup, has zero calibration, and provides real-time indoor localization with a median location error of 1.69m.

Key Idea:

The solution UnLoc works on the idea of dead reckoning, WiFi-based partitioning, and urban sensing. It relies on the availability of the sensors in the clients/user's smartphone, for the data (of displacement, direction, and time) and an unsupervised (recursive) learning model to which the data is fed. The thought behind this solution is that there exist, naturally, some identifiable signatures in the environment from the multiple sensors and access points around us, as the WiFi access point can be overheard, there can be magnetic fluctuations, and our phone has magnetometer sensors as well as the accelerometer, etc. that can be used to identify (relatively if not absolutely) the landmarks inside the building. Initially, we set the Seed Landmarks (SLMs), and as the user moved the data from the sensors can be used to track the distance between these landmarks using a dead-reckoning scheme. As UnLoc gets more and more data, it will start setting Organic Landmarks (OLMs); hence, the distance between SLMs will reduce, thereby reducing the error scope from the dead-reckoning scheme. This way as the data set increases the level of accuracy of the UnLoc increases although, initial users will experience some inferior location accuracy.

Important Details:

1. We are depending on the data from various sensors to apply unsupervised learning (using the k-means clustering algorithm).
2. The factor of error that comes along with dead-reckoning can be significantly high. So, when the user reaches an SLM the location gets reset to the correct location of the landmark, this way the localization error is dropped to zero from the peak as the user.

3. To enable location recalibration, UnLoc aims to exploit the small WiFi landmarks, as in smaller locations the phone error will also be small.
4. Magnetic and Accelerometer landmarks are used to identify the type of motion, if it's walking, running, elevator, stairs, stationary, etc, and the SLM detection module is used to define a sensor pattern that is global across all buildings.
5. A finite State Machine (FSM) is developed to recognize elevator motion patterns.
6. Dead Reckoning required the user's displacement to be calculated, for which UnLoc uses the step size based on the user's height and weight.
7. UnLoc uses an OLM detection algorithm that relies on the recognition of different patterns from many sensed signals.

<u>My Thoughts and Criticism:</u>

The paper indeed presents some great work in the field with relevant observations and proofs. The paper provides an unbiased view of the critics, loopholes, and future work, which demonstrates a great mindset. It can be observed very clearly that the author has tried to be open about his ideas and thought process on the factors ignored, and possible counters/critics of the work done as he has already mentioned that for the analysis the data sets lack diversity of paths, etc.

A few of the assumptions and scenarios that led me to questions and thinking are:

1. Data Privacy can be a key concern in UnLoc. The user's mobile phone is literally using every possible way to get information about the user's movement – displacement, direction, time, etc. (to identify the landmarks).
2. UnLoc needs combined estimates from multiple phones to have more accurate landmarks and as different users will have different devices therefore the error margin will also depend on the factors like the quality of the device and its sensors, comparability of the device software (although the paper mentions that device compatible drivers can be used – as future work vision) but not all phone have similar sensors, therefore, depending on the model the number of signatures and estimates can vary.
3. Experiment observations are taken on a relatively smaller scale and with less audience participation.
4. With each building/new location, the application would need to learn recursively again and create new landmarks and accuracy and the same goes if the building infrastructure/design is significantly changed, the OLMs will be unstable and hence signatures change faster than they can be learned.
5. UnLoc aims to exploit small areas as Wi-Fi landmarks to reduce location error, but what if there is a lack of such small areas?
6. Most of the observations are made in a limited test environment (basically a university). Mostly the Universities have better infrastructure, better Wifi zones, etc. than most other

public places/houses where actual indoor localization would be needed. I believe the test results can vary based on the building design and type. Therefore, the experiment should be performed in a diverse setting.

7. There are multiple variables in this solution, which can add up the error in the location, as data from multiple sensors can be noisy, we might miss some landmark tracking which can lead to issues in resetting the error due to dead-reckoning or maybe error due to wrongly computed step size/count estimates of the user.
8. To identify the similarity of the Wi-Fi Landmarks the paper uses a threshold on similarity (S) which is chosen as 0.4 but this choice of threshold is made from the analysis of only 2 University buildings. In an actual setting, this setup might be different so the threshold can be a variable factor from building-to-building setting.
9. UnLoc can activate with one point of discussion but if the building has multiple entries and users can enter from multiple entries then the relative time of computation (using supervised learning with only 1 point of discussion) can be relatively huge and might require bulky data set.
10. In the experiment setting the analysis and observations are done with each user having two phones (one in the pocket, another in the hand pointing screen facing upwards). In an actual setting, a user might not carry more than 1 phone and hence results might vary.

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