T-101.5241 Assignment 2: Mobile Sensing

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1 Wi-Fi Fingerprinting

Most localization services have relied on GPS to find out the exact location of the device. However, in some scenarios like indoor environments it is practically impossible to receive a good GPS signal and calculate the location. Instead, several indoor location solutions have been proposed. Researchers have developed systems for indoor localization based on many technologies such as FM radio [1], Bluetooth[2], GSM[3, 4, 5, 6], Wi-Fi[3], RFID tags[7], acoustic background spectrum[8], geomagnetism[9] or powerlines[10].

In this report, we focus on a solution based on Wi-Fi fingerprints. First we perform a literature review of proposed methods and algorithms, we assess their strengths and weaknesses, we present commercial solutions, and finally we compare it with GSM and FM fingerprint solutions.

1.1 Overview

Wi-Fi fingerprinting is performed by collecting the Received Signal Strength (RSS) for all the available access points (AP) at one location. The RSS can then be normalized or post-processed in any other way before storing it, and the location at which it was recorded in a fingerprint database. A user or device can then use an algorithm to query the fingerprint database and find the approximate location of a fingerprint.

There exist two main approaches for location fingerprinting: deterministic and probabilistic [11]. For the deterministic method the nearest neighbor algorithms is used. This algorithm calculates the distance between data points, and finds the location based on which one has the closest matching RSS fingerprint. The probabilistic approach is using Bayesian inference. In this approach, the main idea is to calculate the posterior probability for each location[12]. An estimation then becomes the probability that the RSS fingerprint can be found in a location. The location with the highest probability of having such a RSS fingerprint is thus selected as the estimated location.

Usually, the first step in these fingerprinting solutions is to map the area and perform measurements over a grid, and these results are then fed into the fingerprint database.

1.2 Weaknesses and strengths

One of the common weaknesses is the need to perform a training where data has to be collected from the location in order to build the fingerprint database. This process can be time consuming and tedious. Another weakness is that different Wi-Fi devices measure the RSS differently, and thus they must be calibrated in order to correctly estimate the locations. Also, Wi-Fi signals are not usually very strong, and many APs are required for larger areas.

The main strength of the Wi-Fi fingerprinting approach is the pervasiveness of Wi-Fi. In addtion, most devices nowadays possess Wi-Fi capabilities. This enables the Wi-Fi fingerprinting method to be used in a wide array of devices and locations.

1.3 Commercial solutions

There exist several commercial solutions that implement Wi-Fi fingerprinting:

- **Ekahau** Originally they developed and sold a system to locate devices within closed spaces that depended completely on Wi-Fi, and now they provide a solution based on their own probabilistic positioning algorithm[13].
- **Mozilla Location Service** Mozilla keeps an open database of access points for localization.
- **Google Location Service** Google keeps an open database for localization which is fed with data from Android smartphones.
- **Apple** Apple has acquired a company called WifiSLAM. WifiSLAM's solution combined data from several sensors and Wifi-Fingerprinting in order to then process it with machine learning algorithms to create the indoor maps[14].
- **AeroScout** AeroScout provides an RFID Asset Tracking Solution. They use Wifi-Fingerprinting to track the location of assets with active RFID tags[15].

1.4 Comparison against GSM fingerprinting

Although GSM fingerprinting benefits from established databases of known base stations, the accuracy of this approach is within 30 meters[3]. On the other hand, GSM cells are far more stable than Wi-Fi networks, which degrade over time[6]. In addition, GSM signals travel for far greater distances than 802.11. This makes GSM localization work over greater areas than 802.11[6]. Veljo Otsason et al. showed that by using all the detectable GSM cells instead of only the strongest and usable ones the GSM localization system can achieve an accuracy ranging from 2.48m to 5.44m[6].

1.5 Comparison against FM fingerprinting

Localization using FM fingerprinting also benefits from the fact that FM signals travel great distances. This means that with less signals, they cover a wider area. However, this benefit also comes with a disadvantage, and that is that the accuracy can be off by hundreds of meters. In practice, the accuracy obtained with FM localization was higher than Wi-Fi, but the best approach was to use both Wi-Fi and FM fingerprinting at the same time[1, 16]. FM stations, similarly to GSM, are also more stable and degrade less over time, thus requiring less calibration[1]. FM signals are also considered to be more energy efficient and are often allowed in sensitive environments, whereas Wi-Fi is not[16]. Conversely, hardware access, or availability, in modern devices to FM signal data is not nearly as widespread as Wi-Fi.

2 Our Application

2.1 Device Information

- **OS**: Android 4.4
- **Manufacturer**: HTC
- **Sensors**: Magnetic field sensor, magnetic field uncalibrated sensor, 3-axis accelerometer sensor, significant motion sensor, proximity sensor, light sensor, gyro sensor, 9-axis orientation sensor, rotation sensor, linear acceleration sensor, gravity sensor, gyro sensor uncalibrated, game rotation vector sensor, and gesture sensor.

2.2 Wifi Fingerprint Comparison

We used the phone described above to obtain Wifi fingerprint on 2 different times in the Playroom: (1) in the early afternoon of a weekday when there were many people in the building, and (2) at late afternoon of a weekend day when there were only few people in the building.

We observe that of the two moments, the signal level of most WiFi fingerprints during the weekend is slighly better. The number of WiFi fingerprints which were visible to the phone during the weekend is also higher than that of the weekday (38 compared to 34).

2.3 Our Indoor Localization Algorithm

In order to detect the location using WiFi fingerprints, we used k-nearest neighbor algorithm. Our solution consists of 2 steps: data model creation and localization.

- **Data model creation**: for each room, we need samples of WiFi fingerprint list obtained in the room. From the sample list, we form a model containing a list of vectors, each of which contains the information of a WiFi fingerprint sample.
- **Localization**: in order to identify the location, a sample vector of the available WiFi fingerprints at the location is needed. We calculate the Euclidean distance between this vector and all vectors of the data models. The room with the smallest distance is considered the estimated location.

  Note that we only take into account the data vectors which has more than 70% common WiFi fingerprints with the sample vector. From our experiment, this number brings better result than other percentage values.

2.4 Experiements

Given data

We applied the algorithm on the given reference and measurement data. The reference data was used to create the data models. The algorithm estimated the approximate location for measurement data of room A126 and A150 are room A130 and room A141 respectively.

Our data

We built a calibration database using our mobile device. We came to 6 rooms in the A corridor of the CS building, including A120, A121, A125, A133, A137, and A141, and recorded WiFi fingerprints in front of each room. At each position, we did the measurements of the WiFi information 15 times with 5 seconds interval.

We experimented our algorithm with this data set at 10 random points in the corridor and obtained good results with 90% accuracy.

References

[1] Yin Chen, Dimitrios Lymberopoulos, Jie Liu, and Bodhi Priyantha. Fm-based indoor localization. In *Proceedings of the 10th International Conference on Mobile Systems, Applications, and Services*, MobiSys '12, pages 169–182, New York, NY, USA, 2012. ACM.

[2] Lauri Aalto, Nicklas Göthlin, Jani Korhonen, and Timo Ojala. Bluetooth and wap push based location-aware mobile advertising system. In *Proceedings of the 2Nd International Conference on Mobile Systems, Applications, and Services*, MobiSys '04, pages 49–58, New York, NY, USA, 2004. ACM.

[3] Anthony LaMarca, Yatin Chawathe, Sunny Consolvo, Jeffrey Hightower, Ian Smith, James Scott, Timothy Sohn, James Howard, Jeff Hughes, Fred Potter, Jason Tabert, Pauline Powledge, Gaetano Borriello, and Bill Schilit. Place lab: Device positioning using radio beacons in the wild. In *Proceedings of the Third International Conference on Pervasive Computing*, PERVASIVE'05, pages 116–133, Berlin, Heidelberg, 2005. Springer-Verlag.

[4] H. Laitinen, J. Lahteenmaki, and T. Nordstrom. Database correlation method for GSM location. In *Vehicular Technology Conference, 2001. VTC 2001 Spring. IEEE VTS 53rd*, volume 4, pages 2504–2508 vol.4, 2001.

[5] A. Varshavsky, Anthony LaMarca, Jeffrey Hightower, and E. de Lara. The skyloc floor localization system. In *Pervasive Computing and Communications, 2007. PerCom '07. Fifth Annual IEEE International Conference on*, pages 125–134, March 2007.

[6] Veljo Otsason, Alex Varshavsky, Anthony LaMarca, and Eyal de Lara. Accurate GSM Indoor Localization. In *Proceedings of the 7th International Conference on Ubiquitous Computing*, UbiComp'05, pages 141–158, Berlin, Heidelberg, 2005. Springer-Verlag.

[7] Guang-yao Jin, Xiao-yi Lu, and Myong-Soon Park. An indoor localization mechanism using active rfid tag. In *Proceedings of the IEEE International Conference on Sensor Networks, Ubiquitous, and Trustworthy Computing -Vol 1 (SUTC'06) - Volume 01*, SUTC '06, pages 40–43, Washington, DC, USA, 2006. IEEE Computer Society.

[8] Stephen P. Tarzia, Peter A. Dinda, Robert P. Dick, and Gokhan Memik. Indoor localization without infrastructure using the acoustic background spectrum. In *Proceedings of the 9th International Conference on Mobile Systems, Applications, and Services*, MobiSys '11, pages 155–168, New York, NY, USA, 2011. ACM.

[9] Jaewoo Chung, Matt Donahoe, Chris Schmandt, Ig-Jae Kim, Pedram Razavai, and Micaela Wiseman. Indoor location sensing using geo-magnetism. In *Proceedings of the 9th International Conference on Mobile Systems, Applications, and Services*, MobiSys '11, pages 141–154, New York, NY, USA, 2011. ACM.

[10] Erich P. Stuntebeck, Shwetak N. Patel, Thomas Robertson, Matthew S. Reynolds, and Gregory D. Abowd. Wideband powerline positioning for indoor localization. In *Proceedings of the 10th International Conference on Ubiquitous Computing*, UbiComp '08, pages 94–103, New York, NY, USA, 2008. ACM.

[11] M.B. Kjaergaard and C.V. Munk. Hyperbolic location fingerprinting: A calibration-free solution for handling differences in signal strength (concise contribution). In *Pervasive Computing and Communications, 2008. PerCom 2008. Sixth Annual IEEE International Conference on*, pages 110–116, March 2008.

[12] Fangfang Dong, Yiqiang Chen, Junfa Liu, Qiong Ning, and Songmei Piao. A calibration-free localization solution for handling signal strength variance. In Richard Fuller and XenofonD. Koutsoukos, editors, *Mobile Entity Localization and Tracking in GPS-less Environnments*, volume 5801 of *Lecture Notes in Computer Science*, pages 79–90. Springer Berlin Heidelberg, 2009.

[13] Ekahau. Real Time Location Technology. `http://www.ekahau.com/real-time-location-system/technology`, 2014. [Online; accessed 06-December-2014].

[14] Matthew Panzarino. What exactly WiFiSLAM is, and why Apple acquired it. `http://thenextweb.com/apple/2013/03/26/what-exactly-wifislam-is-and-why-apple-acquired-it/`, 2014. [Online; accessed 06-December-2014].

[15] Aeroscout. RFID Asset Tracking Solution. `http://www.aeroscout.com/asset-tracking`, 2014. [Online; accessed 06-December-2014].

[16] Aleksandar Matic, Andrei Papliatseyeu, Venet Osmani, and Oscar Mayora-Ibarra. Tuning to your position: FM radio based indoor localization with spontaneous recalibration. In *Pervasive Computing and Communications (PerCom), 2010 IEEE International Conference on*, pages 153–161. IEEE, 2010.