Indoor positioning using off-the-shelf FM radio devices

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1 Introduction

Indoor localization is important for many areas of ubiquitous computing research, such as activity recognition and prediction, assisted health care, tracking of people and objects, and others. The current de-facto standard of indoor positioning are Wi-Fi–based solutions. However, Wi-Fi coverage is limited in rural areas, developing countries and interference-sensitive environments. In cases when Wi-Fi infrastructure is not readily present, its deployment is expensive both in terms of hardware costs and required personnel qualification.

A cost-effective alternative to Wi-Fi is localization using FM radio signals. Short-range FM transmitters are freely available from conventional electronics shops. FM receivers are already present in many mobile devices, including cellphones, MP3 players, pedometers, etc. Moreover, FM receivers are very power-efficient in comparison to Wi-Fi (power consumption is about 15 mW and 300 mW, respectively [1, 2]). In this paper we present the results of experimental comparison of FM and Wi-Fi positioning systems. Also, we describe and evaluate a method for maintaining the system accuracy over time without any additional hardware.

2 FM indoor positioning

To evaluate the performance of FM positioning system, we placed three FM transmitters in corners of our lab (Figure 1). A smartphone with an embedded FM tuner has been used to collect the received signal strength indicator (RSSI) values from each transmitter in different points of the lab. The measurement points formed a grid with 0.5 m step.

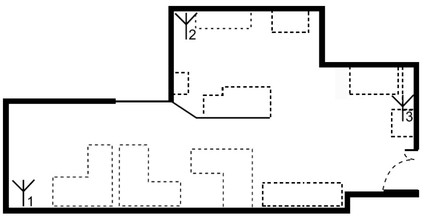

Figure 1: Experimental testbed layout (12 by 6 meters)

For location estimation we employed two machine learning methods, Gaussian processes regression and k-nearest neighbour (kNN) classification. The accuracy of the system has been evaluated using leave-one-out approach. One point was used for testing, while the other points were used as a training set; this was repeated for each point in the dataset. The median accuracy of the system was around 1 m for both methods (see Figure 2).

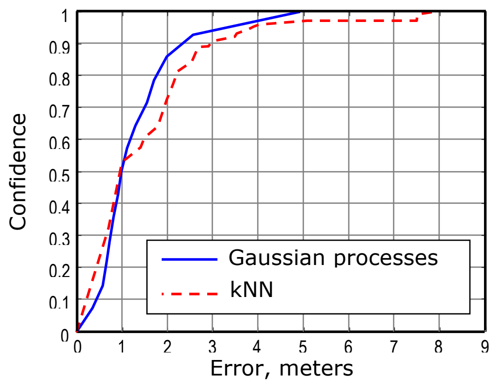

Figure 2: FM positioning accuracy

3 FM versus and with Wi-Fi

To compare the positioning accuracy of FM and Wi-Fi based solutions, we employed the other part of the collected dataset, which comprised

Wi-Fi RSSI fingerprints from Wi-Fi access points collocated with FM transmitters. Unfortunately, due to firmware limitations, the mobile device reported Wi-Fi RSSI rather coarsely (6 distinct values), while FM RSSI had about 50 levels. To mitigate this problem, we reduced the variety of FM RSSI values to 6 levels. This affects the positioning accuracy of FM, but ensures a fair comparison with Wi-Fi.

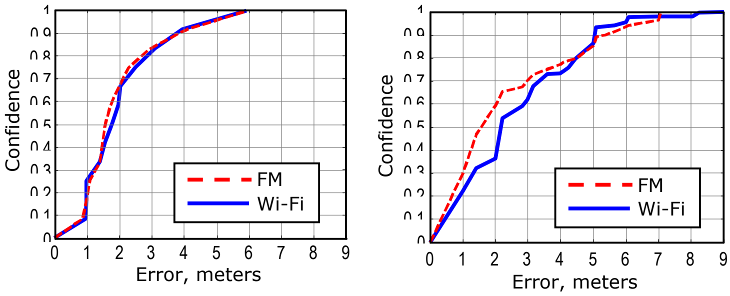

Figure 3: Comparison of FM and Wi-Fi positioning accuracy with Gaussian processes (left) and kNN (right)

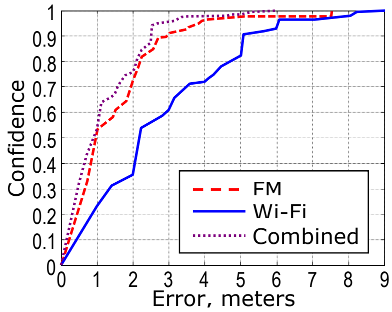

Figure 4: Accuracy of a combined FM+Wi-Fi system (kNN)

The comparison results are presented in Figure 3. As one can see, FM and Wi-Fi positioning have very similar performance. Moreover, when the FM and Wi-Fi RSSI values are merged to form wider fingerprints, the accuracy of such a combined FM+Wi-Fi system is better than any of the underlying technologies alone (see Figure 4).

4 Spontaneous recalibration

A serious issue for fingerprinting-based systems is the temporal instability of RSSI fingerprints, which causes accuracy degradation. To maintain the positioning performance, one needs to perform periodic recalibration of the system, which is a tedious and expensive procedure.

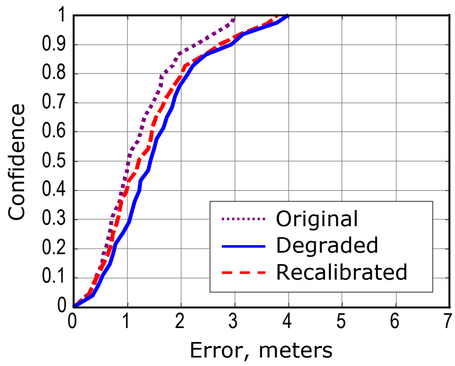

Figure 5: Effect of spontaneous recalibration (Gaussian processes, FM)

In real life, however, the position of the client device can often be inferred from other context sources. For example, the device can detect when it is inserted in a desktop cradle, connected to a wall charger, or placed on a nightstand during nighttime. Knowing the true position of the mobile device, it is possible to update the fingerprint of the current and nearby points (using a simple signal propagation model). Thus the training set is being regularly updated in a way transparent for the user, and without any additional hardware. Figure 5 shows the change of the positioning accuracy over one-month period and the effect of spontaneous recalibration with five known positions.

Acknowledgements

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References

1. TDA7088 Datasheet, 1996.
2. BCM4326 Datasheet. 2006.