Device-Free Indoor Localization Using Ambient Radio Signals

Andrei Popleteev
SnT, University of Luxembourg
4, rue Alphonse Weicker
L-2721 Luxembourg
andrei.popleteev@uni.lu

UbiComp'13 Adjunct, September 8–12, 2013, Zurich, Switzerland.

ACM 978-1-4503-2215-7/13/09...$15.00.

http://dx.doi.org/10.1145/2494091.2497613

Abstract
This paper investigates feasibility of device-free indoor localization using single passive receiver. Instead of local wireless nodes sharing one frequency channel, this work leverages multiple ambient FM radio stations. Experimental results demonstrate feasibility of the proposed approach and highlight the role of frequency diversity for passive localization.

Author Keywords
Device-free localization, passive indoor positioning, FM radio, software-defined radio, frequency diversity

ACM Classification Keywords
I.5.4 [Pattern Recognition]: Applications; C.3 [Special-purpose and application-based systems]: Signal processing systems

Introduction
A large body of research has been dedicated to localization of mobile devices carried by users. However, there are situations when the user does not carry any device (smart environments, assisted daily living). Device-free localization (DFL) methods address the challenge of localizing users without any wearable devices.

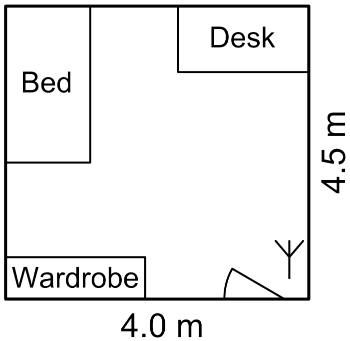

Figure 1: Test environment layout. Antenna symbol indicates location of the receiver.

Radio-based DFL methods are based on effects of radio wave interactions with human body (such as diffraction, reflection, scattering), which ultimately result in measurable changes of signal properties [3]. Current DFL systems require deployment of multiple wireless devices which actively transmit, receive and analyze radio signals [2, 3, 6]. Due to radio spectrum regulations, these devices are typically limited to only one or few frequency channels in a narrow license-free band.

This paper investigates feasibility of DFL with a *single* receiver employing ambient FM radio stations. In contrast to related work, the proposed system is completely passive (since it uses ambient transmitters) and monitors multiple radio channels simultaneously. Multi-frequency scanning is the key feature of the system. The only previous work on ambient FM-based DFL [4, 5] considered only one FM station and found that localization was not possible [5]. In the present paper, 11 FM radio stations are monitored simultaneously with a software-defined radio [1]. Experimental results demonstrate that channel diversity improves localization performance and makes sub-room level localization with ambient stations possible.

The rest of the paper describes the proposed approach, presents experimental results, and concludes with a summary of the findings.

Single-receiver multi-channel DFL

State of the art DFL systems typically employ multiple wireless devices (sensor nodes or Wi-Fi routers) installed around the area of interest. The nodes communicate over one shared radio channel and continuously monitor strength of signals received from other nodes (RSSI). When a person approaches the line between any two nodes, their established RSSI readings change. With the knowledge of node positions and their RSSI levels, user's location can be directly inferred.

This approach is not applicable to the single-receiver passive DFL system, as the system cannot control ambient transmitters nor does it know their locations. Instead, the system exploits multipath radio signal propagation in indoor environments, caused by reflections and interference on walls, furniture and other large objects. Multipath propagation leads to complex map of RSSI distribution within indoor environment. Due to the spatial and frequency diversity of ambient FM transmitters, RSSI distribution maps are different for each frequency channel.

When a person enters the test area, he or she affects radio propagation — in a different way at each frequency, depending on environment properties and person's location. This leads to changes in the signals observed by the DFL system receiver: RSSI readings increase or decrease on particular channels. Machine learning methods can then be employed to recognize locations by their characteristic RSSI patterns, similarly to traditional location fingerprinting methods.

Experimental evaluation

Figure 1 shows the layout of the test environment, a typical apartment room in Luxembourg.

A software-defined radio based on Realtek RTL2832U [1] has been employed to monitor the radio spectrum band from 87 to 111 MHz and to acquire RSSI readings for 200-kHz wide channels. Each sample included 120 channels, of which only 11 active stations were selected for further analysis. For each user location (user sitting at the desk, sitting on the bed, lying in the bed, standing near wardrobe, and being away), we recorded 50 samples with 1-second interval. The data were preprocessed by

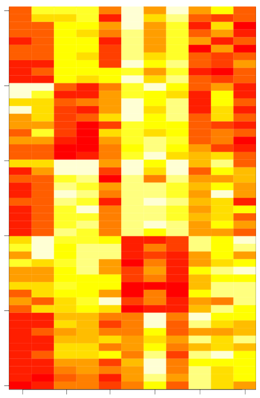

Figure 2: A sample of measured RSSI values for different user locations (one of the eight collected datasets).

averaging groups of 5 consecutive samples into one, and normalizing each channel's RSSI readings to the range of $0 \ldots 1$. After preprocessing, there were ten 11-channel samples associated with each user location (see Figure 2).

Data collection has been performed in four days. Every day we acquired two datasets, with a 20-minute interval between them. All experiments were performed around 1 a.m. in the night to minimize influence of neighboring activities. In total, 8 datasets have been collected.

Visual analysis of the raw data in Figure 2 suggests that each user location has an associated unique pattern of RSSI distribution across channels. The figure also supports the observation of Sigg et al. [5] that single-channel measurements are not likely to provide sufficient distinction between all locations.

In order to recognize locations by their RSSI patterns we tested three classification methods: Gaussian processes, k-nearest neighbor (kNN) with Euclidian distance, and kNN with correlation between samples as a distance measure. The latter provided best accuracy and thus was used for all subsequent experiments.

Same-day vs. next-day performance
First experiments evaluated short-term recognition accuracy. For each of the four same-day dataset pairs, one dataset was used for training and the other one for testing, and vice versa. Median accuracy of all tests was 85%. Table 1 presents the summarized confusion matrix.

The next experiment evaluated localization accuracy of a system tested on the next day after training. Median accuracy among all datasets was 78%. The averaged confusion matrix for all tests is shown in Table 2.

	Ground truth				
Classifier result ↓	empty	desk	bed-lying	bed-sitting	ward-robe
empty	**0.66**	0.08	0.10	0	0.02
desk	0.01	**0.90**	0.02	0.01	0
bed-lying	0.08	0.02	**0.68**	0.04	0.04
bed-sitting	0.11	0	0.10	**0.85**	0.11
wardrobe	0.14	0	0.10	0.10	**0.83**

Table 1: Confusion matrix for same-day testing.

	Ground truth				
Classifier result ↓	empty	desk	bed-lying	bed-sitting	ward-robe
empty	**0.62**	0.08	0.12	0	0.05
desk	0.11	**0.78**	0.12	0.03	0.01
bed-lying	0.09	0.05	**0.56**	0.02	0.03
bed-sitting	0.04	0.08	0.05	**0.83**	0.09
wardrobe	0.14	0.01	0.15	0.12	**0.82**

Table 2: Confusion matrix for next-day testing.

The results indicate that while most of the locations could be recognized with 78–90% accuracy, two states were challenging. Firstly, empty room was often indistinguishable from user standing near wardrobe. Secondly, "lying in the bed" state was often confused with the others. On one hand, both issues might be attributed to relatively weak influence of user's presence on radio wave propagation near large piece of furniture. On the other hand, the described localization approach heavily depends on test environment specifics (layout, receiver placement, FM stations location, frequency and transmission power). These might lead to "blind spots" where user's presence has minimal impact on signal propagation. Detailed understanding of these factors requires further investigation.

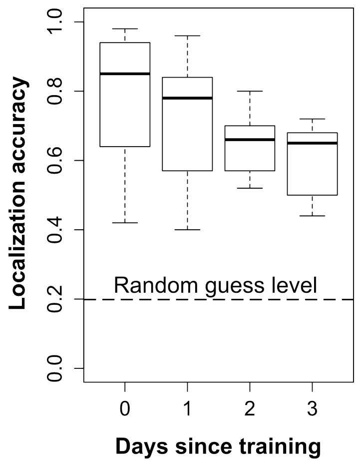

Figure 3: Accuracy degradation with time.

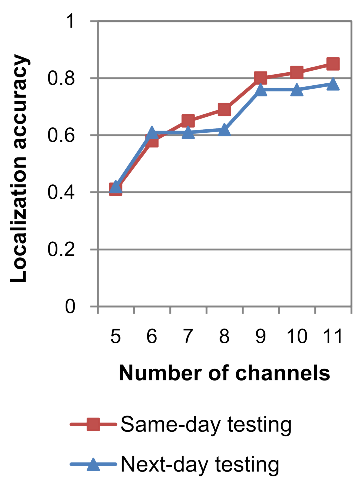

Figure 4: Accuracy dependence on number of channels.

Accuracy degradation with time

Wireless localization systems are sensitive to changes in the environment (such as temperature, humidity, movement of people, doors, furniture, other objects) which lead to degradation of localization performance. A system based on remote transmitters might also be affected by changing weather conditions and movement of outdoor objects.

To evaluate temporal stability of the localization performance, we trained and tested the system using datasets separated by several days. Box-and-whisker plot in Figure 3 presents summarized results for all the possible dataset combinations. According to the results, three days after the training the median localization accuracy decreased from 85% to 65%. Nevertheless, even worst-case results remained well above the baseline level of 20% (probability of randomly guessing the correct location from five alternatives). It should be noted that accuracy degradation is not specific for the proposed system only but rather is a common problem of wireless localization systems and can be mitigated by periodic re-training (either manual or automatic).

Number of channels

As mentioned earlier, wireless localization systems could benefit from frequency diversity. Figure 4 shows localization performance of the proposed system when only a subset of available frequency channels is used. When all 11 channels were employed, the system could distinguish empty room and four sub-room level locations with 85% accuracy. However, with 5 channels the performance decreased to only 40%. Thus, the experimental results confirm the initial intuition and prove that additional frequency channels can considerably improve localization accuracy.

Conclusion

This paper demonstrated feasibility of device-free localization with a single passive receiver and multiple ambient FM radio stations. The experimental results show that frequency diversity plays an essential role in a DFL system and can considerably improve localization performance.

This work will continue with long-term performance tests and feasibility study of fine-grained passive DFL.

References

[1] RTL-SDR. `http://sdr.osmocom.org/trac/wiki/rtl-sdr`.

[2] Kosba, A. E., Saeed, A., and Youssef, M. Rasid: A robust WLAN device-free passive motion detection system. In *Proc. PerCom-2012*, IEEE (2012), 180–189.

[3] Scholz, M., Sigg, S., Schmidtke, H. R., and Beig, M. Challenges for device-free radio-based activity recognition. In *Proc. CoSDEO-2011 (in conjunction with MobiQuitous 2011)*, Springer (2011).

[4] Shi, S., Sigg, S., and Ji, Y. Passive detection of situations from ambient FM-radio signals. In *Proc. UbiComp-2012*, ACM (New York, NY, USA, 2012), 1049–1053.

[5] Sigg, S., Scholz, M., Shi, S., Ji, Y., and Beigl, M. RF-sensing of activities from non-cooperative subjects in device-free recognition systems using ambient and local signals. *IEEE Trans. Mobile Computing*, PrePrints (2013), 1–14.

[6] Wilson, J., and Patwari, N. See-through walls: Motion tracking using variance-based radio tomography networks. *IEEE Trans. Mobile Computing 10*, 5 (2011), 612–621.