Passive, Device-Free Recognition on Your Mobile Phone: Tools, Features and a Case Study

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Abstract. We investigate the detection of activities and presence in the proximity of a mobile phone via the WiFi-RSSI at the phone. This is the first study to utilise RSSI in received packets at a mobile phone for the classification of activities. We discuss challenges that hinder the utilisation of WiFi PHY-layer information, recapitulate lessons learned and describe the hardware and software employed. Also, we discuss features for activity recognition (AR) based on RSSI and present two case studies. We make available our implemented tools for AR based on RSSI.

Keywords: Activity recognition · Passive device-free recognition

1 Introduction

In urban areas, a mobile device is constantly exposed to (possibly encrypted) communication. In contrast to traditional communication, where such data is considered as noise or congestion, we exploit implicit information on environmental situations carried by the signal strength fluctuation of overheard packets.

Fluctuation on WiFi RSSI might indicate presence, the number of people around or even activities conducted in proximity (cf. Fig. 1).

Localisation of objects and individuals [11] as well as the classification of activities [13] or crowd counting [15] has been considered recently. We distinguish between systems utilising software-defined-radio (SDR) devices to sample the fluctuation in a received signal and systems leveraging information available from received data packets. In the former case, due to the higher sampling frequency and additional information available, the recognition accuracy is generally higher. However, these systems require specialised SDR devices.

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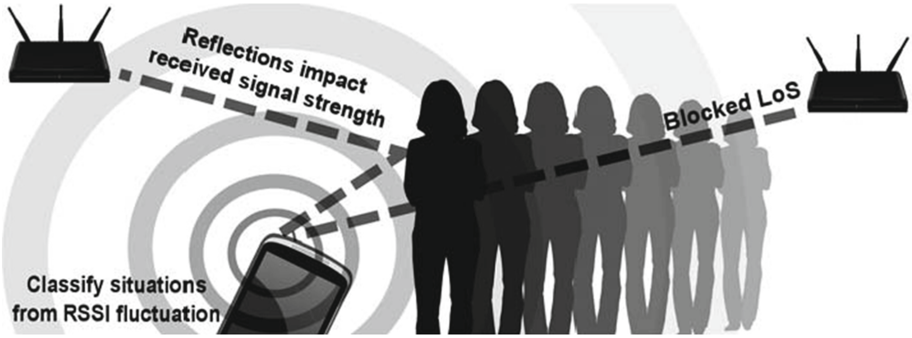

Fig. 1. Illustration of the recognition of activities via RSSI fluctuation

We recognise activities on a single device (a mobile phone) from packets broadcast by a transmitter not under our control (a WiFi access point (AP)). In particular, we investigate the frequency of received packets and the distance between the receiver and the passive subject monitored performing activities as well as the impact of utilising RSSI from multiple APs. The contributions are

(1) the presentation and discussion of Python-tools to visualise and process captured RSSI data for the recognition of environmental situations
(2) a discussion of accuracy achieved from RSSI sampled on a mobile phone
(3) an implemented toolchain for RSSI-based device-free passive recognition

This is the first study to demonstrate the recognition of activities in a passive, device-free, RSSI-based system and the first to leverage an off-the-shelf phone.

2 RF-based Device-Free Recognition

The recognition of movement, activities and gestures from RF-channel features induced by individuals in proximity not equipped with a transmit or receive device is generally referred to as device-free-radio-based recognition [10,11,13].

For instance, Sigg et. al recognise activities from the fluctuation of a continuous signal in [12]. The authors utilise the distance between signal peaks, the RMS, the third central moment and the entropy of a received signal as distinguishing features. With multiple receive antennas, also multiple activities conducted simultaneously can be distinguished [13]. Although Adith et al. demonstrated that time diversity can compensate for missing spatial diversity in a single antenna system [1], multiple antennas generally enable advanced recognition techniques. For instance, Hong et. al distinguish a moving individual at four different locations by applying random matrix theory on the received signal vectors from multiple antennas [2]. Pu and others demonstrated the accurate distinction of gestures via micro-Doppler variations from narrow-band signals [4,7].

These studies use highly accurate information on the wireless channel obtained by SDRs. Such hardware is typically missing in consumer mobile devices.

Focusing instead on RSSI fluctuation which is commonly available at contemporary wireless devices, Patwari and others estimated the breathing frequency of an individual from the RSSI of packets exchanged by surrounding nodes [6]. Each node in a token-passing protocol transmitted packets at about 4 Hz (resulting in packet transmission at 80 Hz when considering all nodes). Authors have predicted the count of up to 10 stationary or moving individuals [15] from RSSI within a field of sensor nodes. Other studies consider the detection of activities (*standing, sitting, lying, walking* and *empty*) from RSSI in a sensor network [8]. These systems utilise dedicated transmit and receive nodes and therefore have full control on the size, payload and frequency of packets transmitted [9].

In a passive, mobile phone-based system, channel access is restricted to the RSSI or other link quality indicators. These values are computed in the wireless interface at the receiver with every incoming packet. Clearly, this means that the sampling rate and the accuracy of the available data is severely reduced.

Another challenge is the access to the WiFi hardware since firmware with access to WiFi parameters is sparse. Also, standard mobile phone operating systems prevent root access to the phone's hardware, which is required to run the interface in monitor mode. More severe even, most handsets utilise the same chipset family (e.g. Broadcom bcm4329, bcm4330(B1/B2), bcm4334, bcm4335) for which the default firmware does not provide access to the desired information.

The use of an external antenna would mitigate these problems[1]. However, since this solution considerably extends the dimensions and complexity of the hardware utilised, we instead used a modified firmware for the above mentioned Broadcom chipset family that allows to run a WiFi interface in monitor mode [3].

We installed this firmware on a Nexus One running Cyanogen mod 7.2 and used tcpdump on the interface in monitor mode to capture RSSI of received packets. In monitor mode, no data can be transmitted so that no impact can be taken on the frequency of received packets. We can, however, adjust the channel monitored and utilise multiple APs on the same channel.

To-date, there is no study on passive device-free RF-based AR that leverages RSSI from environmental sources not under the control of the system. Moreover, there is no such system running on a mobile phone. We report our experiences in designing such a system and discuss challenges encountered.

With RF-based recognition on mobile phones, RF-based sensing can be broadly applied for the recognition on hardware we all carry around constantly.

3 Tools for RSSI-based Activity Recognition

We developed tools to process RSSI data. All tools are written in Python and are available for download[2]. They consist of multiple loose coupled components which are glued together by importing them into an encasing python script, that defines the workflow (cf. Fig. 2). The tools cover the following tasks:

[1] https://github.com/brycethomas/liber80211/blob/master/README.md
[2] All tools are available at http://www.stephansigg.de/Mobiquitous2013.tar.gz

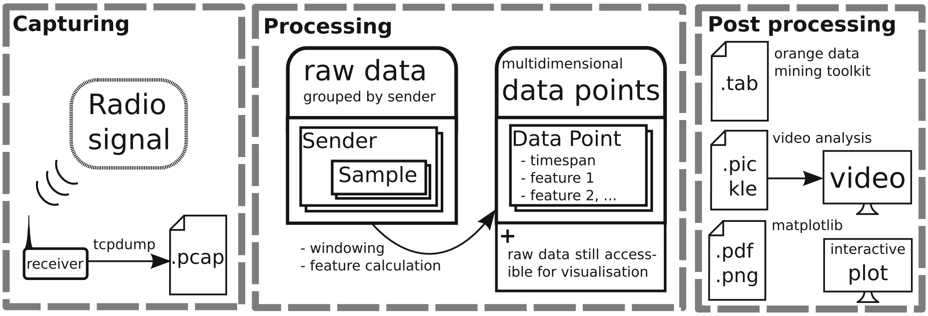

Fig. 2. Schematic overview on the functionality and workflow of our tools

- Obtain RSSI data and other meta-data from *pcap files*
- Classification, filtering and grouping of packet-data (from the pcap files)
- Feature calculation
- Feature export for the *orange* data mining toolkit[3]
- Graphical analysis of features and raw data
- Video analysis of features and raw data

Now we describe how these tasks are achieved and how to reuse components.

3.1 The Pcap Parser

An external capturing tool should be used to record traces of the radio data. It is important to use a WiFi adapter in *monitor mode* since otherwise it performs Ethernet emulation; radio specific information, like RSSI values, are not accessible then. We assume that captured traces are stored in the *.pcap* format.

The pcap files are read by the component *Pcap_Parser.py*. The function *Pcap_Parser.parse* takes a pcap-filename and optionally the number of packets to read, as input. It returns a dictionary[4] indexed by the sender mac address and storing objects of type *Storage_Classes.Sender*, defined in *Storage_Classes.py*. Such object holds metadata[5] about senders and the samples gained from them: *Storage_Classes.Sample* stores RSSI, timestamp, packet type and data rate.

The parsing itself is done by the external library *pcapy*[6] which interfaces *libpcap*[7]. It is also capable of live packet capturing.

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[3] http://orange.biolab.si/
[4] A *dictionary* (or *associative array* is a python data type holding key-value pairs.
[5] Sender metadata: Type [station, access point, unknown]; Mac Address; SSID
[6] http://corelabs.coresecurity.com/index.php?action=view&type=tool&name=Pcapy
[7] http://www.tcpdump.org/

3.2 Data Grouping and Feature Calculation

Since the pcap parser clusters the data by sender and determines the types of these senders, APs with the highest packet count can be picked easily.

Based on the timestamps, samples can be grouped to *units*. Units are non-overlapping and contain all samples received in a fixed timespan. This can be used to normalize non-uniform sample rates; units that contain too few samples can also be dropped. Timestamp-based annotation data can be assigned to the respective units, too. These steps are implemented in the *Data_Grouping.py* component within the function *Data_Grouping.build_units*.

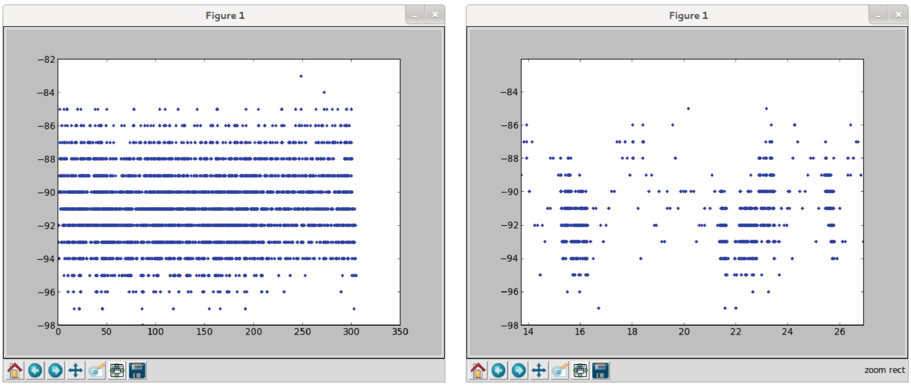
Further grouping can be done with the function *Data_Grouping.windowing*. This function takes a list of units, the desired window size and a boolean value determining possible overlap. Overlapping windows have an offset of one unit. Feature calculation is based on these windows. Several *features* are already implemented in the *Features.py* component, including: *mean*, *variance*, *sign*. Multiple features can be combined to one (multidimensional) data point by the function *Features.calculate_features*. It returns a list of *Data_Classes.Data_Point*.

Finally, units, windows and data points can be stored using Python's *pickle* module[8]. The later described video analysis tool takes this as input.

3.3 Visualization and Export

The calculated features, as well as the raw RSSI data can be plotted by the component *Visualization.py*. For this, the external library *matplotlib*[9] is used. It comes with an interactive plotting mode and various export modules.

Figure 3 displays the interactive plotting mode; in Fig. 3a the whole recording (5 min) is displayed, Fig. 3b shows a zoomed-in part (13 s). PDF-exports of features and raw data is supported. The module *Orange_Export.py* exports the features for post-processing in the *orange* data mining toolkit.



(a) Recorded RSSI data of a complete file (b) Subset of the same file zoomed in

Fig. 3. Visualisation of RSSI raw data in the interactive plot

[8] http://docs.python.org/2/library/pickle.html

[9] http://matplotlib.org/

3.4 Video Analysis Tool

Even recognition algorithms based on machine learning depend on human expert knowledge. A set of meaningful features is chosen manually and calculated over the raw data in advance. To choose such features a human expert has to gain knowledge on how the information about the different states (e.g. performed activities) are contained in the data. The video analysis tool is supposed to help with this task.

By observing the evolution of raw data as a video stream, a human can develop an intuitive comprehension about similarities and differences of the data points during different states/activities. Also, the video analysis tool can show preprocessed data to provide insight in different aspects of the data (for instance, histograms). This can be used to investigate possible interim stages and eventually to develop a new meaningful feature for the problem. If data is tagged, tags can be associated with colors.

4 Case Study: Device-Free Passive Recognition on Phones

We conducted case studies in indoor environments at ETH Zurich and TU Braunschweig. For the recognition we utilised a Nexus One with Cyanogen mod 7.2 and the WiFi driver of [3]. For our case study at ETH Zurich (Sect. 4.2), we were interested in the sample rate required for RSSI-based recognition. The study was conducted over four days with repetitions of each experiment on the consecutive days. The phone was placed on a table but exact position and orientation of the phone and surrounding objects was intentionally altered.

The case studies described in Sect. 4.3 were conducted at TU-Braunschweig over two consecutive days with repetitions of experiments on both days. We investigated the impact of the distance of an individual to the phone. For this, we fixed the location of the phone but altered the surrounding furniture (chairs, tables, board). On the floor, locations were marked in increasing distance of 0.5 m up to 4.0 m. At these locations, an individual would walk around or perform gestures for at least 5 min. In addition we exploited that two APs were present in this scenario to investigate the impact of the choice of the AP.

4.1 Suitable Features for RSSI-based Recognition

We initially considered a set of 18 features. Figure 4 details the most relevant of those. Features were generated over a window of 20 RSSI samples each. We applied a feature subset selection process utilising a relief function with 20 neighbours and 50 reference examples. By this, the feature set has been reduced to a set of 12 features (cf. Table 1). Additionally, we manually exploited combinations of the resulting features to identify those which are most expressive.

Several combinations of the features *mean, median, variance, maximum* and the *difference between minimum and maximum* achieved best classification results.

Assume that $\mid \mathcal{W}_t \mid$ samples s_i are taken on the signal strenth of an incoming signal for a window $\mathcal{W}_t = s_1^t, \dots, s_{|\mathcal{W}_t|}^t$

Mean signal strength

The mean signal strength over a window of measurements represents static characteristic changes in the received signal strength.

It provides means to distinguish a standing person as well as her approximate location.

$$\text{Mean}(\mathcal{W}_t) = \frac{\sum_{s_i \in \mathcal{W}_t} s_i}{\mid \mathcal{W}_t \mid}$$

Variance of the signal's strength

The variance of the signal strength represents the volatility of the received signal.

It can provide some estimation on changes in a receiver's proximity such as movement of individuals

$$\text{Var}(\mathcal{W}_t) = \sqrt{\frac{\sum_{s_i \in \mathcal{W}_t} (s_i - \text{Mean}(\mathcal{W}_t))^2}{\mid \mathcal{W}_t \mid}}$$

Standard deviation of the signal's strength

The standard deviation can be used instead of the variance. The interpretation of these two features is identical

$$\text{Std}(\mathcal{W}_t) = \sqrt{\text{Var}(\mathcal{W}_t)}$$

Median of the signal's strength

The median signal strenth over a window of measurements represents static characteristic changes in the received signal's strenth. It is more robust to noise than the mean.

It provides means to distinguish a standing person as well as her approximate location.

We define the ordered set of samples as

$$\mathcal{W}_{t,\text{ord}} = \overline{s_1}, \dots, \overline{s}_{|\mathcal{W}_t|} \ ; \ i < j \Rightarrow s_i \leq s_j$$

From this, the median is derived as

$$\text{Med}(\mathcal{W}_t) = s_{\lceil |\mathcal{W}_{t,\text{ord}}|/2 \rceil}$$

Normalised spectral energy

The normalised spectral energy is a measure in the frequency domain of the received signal.

It has been used to capture periodic patterns such as walking, running or cycling.

$$\text{E}_i = \sum_{k=1}^{n} \text{P}_i(k)^2$$

Here, $\text{P}_i(k)$ denotes the probability or dominance of a spectral band k:

$$\text{P}_i(k) = \frac{\text{FFT}_i(k)^2}{\sum_{j=1}^{n} \text{FFT}_i(j)^2}$$

As usual, we calculate the k-th frequency component as

$$\text{FFT}_i(k) = \sum_{t=(i-1)n+1}^{in} \text{s}(t) e^{-j\frac{2\pi}{N}kt}$$

Minimum and maximum signal strength

The minimum/ maximum signal strength over a window represents extremal signal peaks.

It can be utilised as an indicator for movement and other environmental changes

$$\text{Min}(\mathcal{W}_t) = s_i \in \mathcal{W}_t \text{ with } \forall s_j \in \mathcal{W}_t : s_i \leq s_j$$

$$\text{Max}(\mathcal{W}_t) = s_i \in \mathcal{W}_t \text{ with } \forall s_j \in \mathcal{W}_t : s_i \geq s_j$$

Signal peaks within 10% of a maximum

Reflections at nearby or remote objects impact the signal strength at a receive antenna. When all peaks are of the similar magnitude, this is an indication that movement is farther away.

This feature can indicate near-far relations and activity of individuals.

$$h(s_i) = \begin{cases} 1 & \text{if } s_i \geq \max(s_1, \dots, s_{|\mathcal{W}|}) \cdot 0.9 \\ 0 & \text{else} \end{cases}$$

$$\text{max}_{0.9}(\mathcal{W}_t) = \sum_{s_i \in \mathcal{W}_t} h(s_i)$$

Fig. 4. Features utilised for the classification of activities. For space limitations, we omit the well known definitions of a signal's fast Fourier transformation and a signal's entropy. Equally, the definition of the third central moment and the difference between subsequent maxima are not listed here for their simplicity.

Table 1. Features and their significance after feature selection

Significance	Feature description
0.023	Maximum signal strength
0.010	Mean FFT
0.003	Normalised spectral energy
0.003	Mean signal strength
0.003	Median of the signal's strength
0.003	Difference between minimum and the maximum in one sample window
0.003	Minimum signal strength
0.002	Standard deviation of the signal's strength
0.002	Variance of the signal's strength
0.002	Signal peaks within 10% of a maximum
0.001	Third central moment
0.000	Entropy

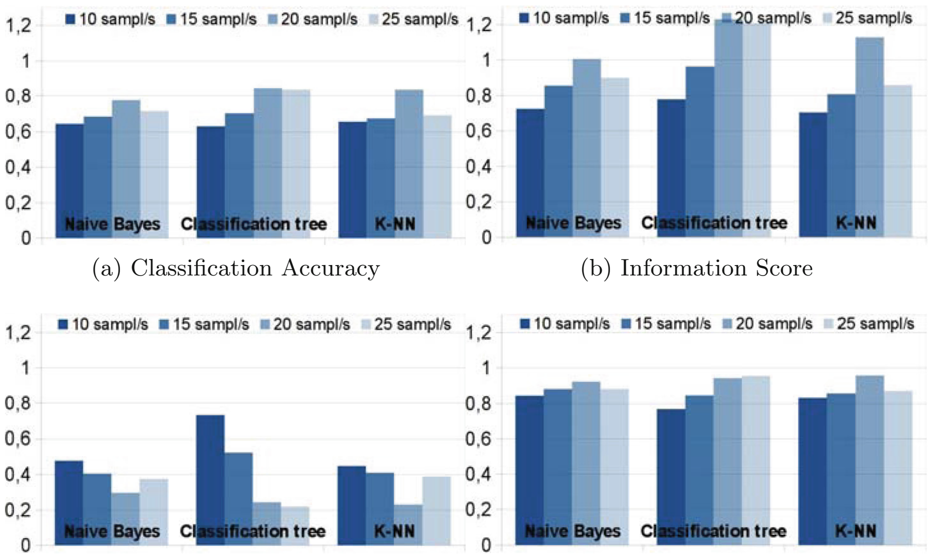
For the case studies, we decided for a feature combination of *mean, variance, maximum* and *difference between maximum and minimum.*

4.2 Impact of the Sampling Frequency

Utilising RSSI from a system not covering a transmitter, one of our main concerns has been the sample rate. Since the receiver has no impact on the number of incoming packets, it has to rely on data connections made by other devices. From our experiments, we frequently captured about 50 to 70 packets per second on one channel (all APs and packet types). Considering only meaningful packets from a single AP, this figure easily dropped below 20 or even 10 on average. In addition, the stream of packets is fluctuating considerably. We might experience a second with only one or two packets followed by one with twice the average number of packets. Clearly, this fluctuation also affects the value calculated for the various features. In order to estimate the impact of a specific sample rate, we kept the window size constant and uniformly ignored or duplicated packets when a desired packet count was not met.

We distinguish between an empty office at ETH Zurich where the mobile phone is lying on a table, the same room with a person walking next to the table and a person holding the phone and handling it. Recordings have been taken over four days at different times of day. Each single activity is sampled for five minutes in a row. This was repeated on each day twice for all activities. Overall, about three hours of continuously sampled data has been produced and was employed for the study.

We utilised a Naive Bayes classifier with 100 sample points and a Loess window of 0.5, a classification tree in the implementation of the orange data mining tool with two or more instances at its leaves and a k-NN classifier with $k = 20$ (best results have been achieved with k between 10 and 20), and a 10-fold cross validation. Figure 5 depicts our results.



(a) Classification Accuracy (b) Information Score

(c) Brier Score (d) Area under the ROC curve (AUC)

Fig. 5. Classification results for the Naive Bayes, classification tree and k-NN classifier. The distinct tables show the performance with distinct sample rates.

The figure details the overall classification accuracy (CA) for all classifiers together with their information score (IS), Brier score and the area under the ROC[10] curve (AUC) as defined by [5,14]. The information score presents a measure of how well the classifier could learn a specific data set. The higher the value, the more often did the classifier predict the correct class. Brier score measures the mean squared difference between a predicted probability for an outcome and the actual ground truth. The AUC describes the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one.

Table 2. Confusion matrices for the Naive Bayes, classification tree and k-NN classifiers with a sample rate (RSSI information) of 20 samples per second

Truth	Classification: activity	empty	holding	recall
activity	**.714**	.007	.279	.71
empty	.007	**.936**	.057	.94
holding	.286	.043	**.671**	.67
precision	.709	.949	.667	

(a) Naive Bayes classifier

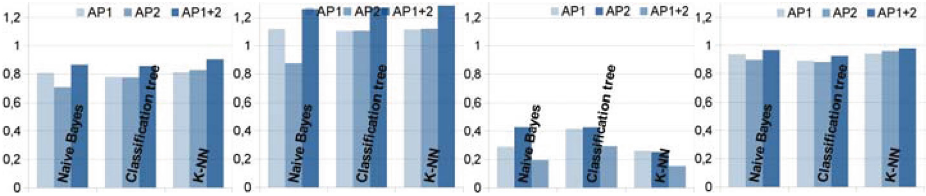
Truth	Classification: activity	empty	holding	rec
activity	**.879**	.007	.114	.88
empty	.029	**.9**	.071	.90
holding	.186	.057	**.757**	.76
precision	.804	.933	.803	

(b) Classification tree

Truth	Classification: activity	empty	holding	rec
activity	**.829**	.014	.157	.83
empty	.021	**.921**	.057	.92
holding	.207	.036	**.757**	.76
precision	.784	.949	.779	

(c) k-NN classifier

[10] Receiver Operating Characteristic.



(a) Classif. Accuracy (b) Information Score (c) Brier Score (d) AUC score

Fig. 6. Classification results for the Naive Bayes, classification tree and k-NN classifier. The distinct tables show the performance with 5 samples/second and for different combinations of data obtained from two access points.

The sample rate impacts these statistics. The values improve up to a rate of 20 samples per second and then worsens again. We account this to the increased fraction of duplicated samples to artificially achieve a steady sample rate over time (samples we added to achieve a steady sample rate). Table 2 details the confusion matrices achieved for the various classifiers in this scenario.

4.3 Impact of the Distance to a Receiver

We also considered in the distance to the WiFi receiver of a mobile phone in which still a recognition is feasible. To this end, we conduct another case study in a lecture room of TU Braunschweig. In the study, the mobile phone is placed on top of a table, capturing packet information while a person is moving in varying distance to the device. We investigated the accuracy to distinguish between an empty environment, the environment with a person moving in 4 m distance and the environment with a person moving closer to the receiving mobile phone. Naturally, the classification accuracy deteriorates when the locations in which activity was performed are closer together (cf. Fig. 6). Table 3 shows for the k-NN classifier[11] that in this setting a person moving in 0.5 m distance can be well distinguished from the empty case and from a person moving in greater distance. While still in 4 m distance the signal received is distinguishable from an empty room, the accuracy is considerably lower.

Table 3. Confusion for activities in different distances to the phone (AP 1; k-NN)

Truth	Classification 0.5m	4.0m	empty	recall
0.5m	**.981**	.019		.981
4.0m	.026	**.768**	.206	.768
empty	.013	.310	**.677**	.677
precis.	.962	.702	.763	

(a) Near and far

Truth	Classification 2.0m	4.0m	empty	recall
2.0m	**.872**	.115	.013	.872
4.0m	.244	**.603**	.154	.603
empty	.077	.205	**.718**	.718
precis.	.731	.653	.812	

(b) Medium and far

Truth	Classification 3.5m	4.0m	empty	recall
3.5m	**.530**	.349	.121	.530
4.0m	.403	**.396**	.201	.396
empty	.154	.188	**.658**	.658
precis	.488	.424	.671	

(c) Greater distance

11 For space constraints, we only depict results of the k-NN classifier. Results with other classifiers have been comparable.

Table 4. Utilising data from another access point in the same scenario

Gr. truth	Classification 0.5m	4.0m	empty	recall
0.5m	**.940**	.034	.027	.940
4.0m	.074	**.732**	.195	.732
empty	.020	.174	**.805**	.805
precision	.909	.779	.784	

(a) AP 2; k-NN classifier

Gr. truth	Classification 0.5m	4.0m	empty	recall
0.5m	**1.0**			1.0
4.0m	.027	**.846**	.128	.846
empty	.007	.134	**.859**	.859
precision	.968	.863	.871	

(b) AP 1+2; k-NN classifier

When the distance to the person moving is increased, naturally, the cases are more likely confused. However, note that in all cases the movement conducted in 4 m distance can be distinguished from the other two cases. Consequently, we conclude that there is a good potential to classify activities also in this distance so that for standard indoor environments a mobile phone can cover a typical room sufficiently.

In the case study described in Sect. 4.3, two dominant APs were present operating on the same frequency. Although the signal strength between both differed by about 10 dBm on average, the classification accuracy reached was comparable using packets from either AP (cf. Tables 3 and 4). However, by utilising the information observed from both APs, it is possible to further tweak the classification performance. We created features considering the data received from both APs simultaneously.

When the results are combined so that features are created from RSSI information from both APs, the accuracy can be further improved (cf. Fig. 6). Tables 4a and b depict the confusion matrices for the k-NN classifier in both cases.

5 Conclusion

We have presented our experiences with the recognition of activities from RSSI samples captured on a mobile phone. This is the first study of a passive RSSI-based AR system and the first to exploit the capabilities of an off-the-shelf mobile phone. In particular, we investigated the impact of the sampling rate, the distance of the observed passive subject and discussed the consideration of RSSI samples from multiple APs. In addition, we published and explained the tools developed in the scope of this study for the use in related research projects. We envision, that this research will open new possibilities for AR since mobile phones are very personal devices carried virtually everywhere and since, unlike with inertial sensors, RSSI-based AR is feasible also when the device is not carried on the body.

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