Leveraging RF-channel fluctuation for activity recognition

Active and passive systems, continuous and RSSI-based signal features

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ABSTRACT

We consider the recognition of activities from passive entities by analysing radio-frequency (RF)-channel fluctuation. In particular, we focus on the recognition of activities by active Software-defined-radio (SDR)-based Device-free Activity Recognition (DFAR) systems and investigate the localisation of activities performed, the generalisation of features for alternative environments and the distinction between walking speeds. Furthermore, we conduct case studies for Received Signal Strength (RSS)-based active and continuous signal-based passive systems to exploit the accuracy decrease in these related cases. All systems are compared to an accelerometer-based recognition system.

Categories and Subject Descriptors

J.9.d [**Mobile applications**]: Pervasive Computing; H.5.5.c [**Information Interfaces and Representation**]: Signal analysis, synthesis, and processing; I.5.4.m [**Pattern recognition**]: Signal processing; J.9.a [**Mobile applications**]: Location-dependent and sensitive

General Terms

Case study

Keywords

Device-free activity recognition, RF-sensing

1. INTRODUCTION

Activity recognition (AR) is among the technologies that can exploit and multiply the potential underlying the current trend towards an Internet of Things (IoT). Environmental stimuli from a multitude of devices can be leveraged for the recognition of activities. In contrast to many current research efforts, most sensors in an IoT are not carried by an individual. Therefore, for AR, sensing hardware to detect activities from individuals not equipped with a device is required (Device-free activity recognition (DFAR)).

We exploit the potential of ubiquitously deployed IoT devices for AR by utilising their RF-interface as a sensor.

Incoming signals are blocked or reflected by a person performing an activity. This leads to fluctuation in the received signal strength. When people conduct activities, thereby moving in specific ways, they induce a characteristic fingerprint on the RF-signals at nearby receivers. We can then leverage the received signal in order to identify such patterns and classify them for the corresponding activity.

RF-based AR can be seen as an enabling technology for smart spaces and intelligent environments. Since virtually all IoT-devices incorporate an RF-interface, there is a tremendous potential for RF-based AR in such an environment. Compared to video-based systems which have been recently deployed for the passive recognition of activities in such spaces, RF-based AR is less privacy violating. Indeed, for a good number of applications the location, activity, count, movement direction or gesture of individuals is needed rather than their identity. RF-sensing has the potential to provide this information without disclosing identity.

We distinguish various DFAR classes conditioned on the topology of the recognition system and the type of data leveraged. In particular, active DFAR systems incorporate a transmitter as part of the recognition system while passive DFAR systems exploit ambient signals. Furthermore, the signals utilised for recognition might be continuous signals modulated onto a wireless carrier (this typically requires a software-defined radio (SDR) device for recognition) or based on features provided with received data packets (frequently, the Received Signal Strength Indicator (RSSI) is utilised). The contribution of this work is

1/ a comparison of active and passive continuous signal-based as well as active RSSI-based DFAR system regarding the recognition of simple activities, walking speeds, localisation of conducted activities

2/ investigation of classification accuracy of an active system that is trained in a different scenario (Ad-Hoc)

3/ Discussion of features suited for various activity classes and DFAR systems

4/ comparison of the active and passive DFAR systems to accelerometer-based AR

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For these case studies, we have utilised mostly time-domain features to allow for a fair comparison to the RSSI-based system. For an RSSI-based system (basically most non-SDR state-of-the-art wireless hardware) frequency domain features are not feasible due to the bursty nature and low-accuracy of the RSSI.

2. RELATED WORK

The recognition of situations or activities from RF-channel fluctuation has its origin in the localisation of individuals based on wireless channel information. Classical approaches for RF-channel-based localisation are device-bound, so that a subject or object to be localised has to carry an RF-receiver. First systems utilised RSSI fingerprints in order to distinguish various locations. Due to the shadowing and blocking of multi-path signals, their superimposition as well as constructive and destructive interference differs for various locations. An early example is the RADAR system that employed signals from WiFi access points [5]. Other authors utilised signals from GSM base stations [15, 34] or FM radio signals [11, 40]. With recent improvements regarding the automation of fingerprinting mechanisms, there are still advances proposed for these approaches [8, 20, 2].

However, much work has shifted towards systems that are capable of real-time on-line localisation of subjects or objects, thereby omitting the time-consuming creation of a fingerprint-map [25, 36, 6]. First results in this direction have been achieved by Woyach et al. who discuss the effect of changes to a static environment on the signal envelope of a received RF signal [38]. Additionally, they show that the velocity of an entity can be estimated by analysing the RSSI pattern of continuously transmitted packets of a moving node. Muthukrishnan and others advanced these studies by distinguishing between moving or stationary nodes via the analysis of the fluctuation of the RSSI in a network of wireless nodes [13]. Anderson et al. and Sohn et al. distinguish also between up to six velocity levels [3, 32]. These device-bound localisation systems can reach remarkable robustness as recently demonstrated by Sen et al. who achieve an accuracy of about 1 meter even while the receive device is carried by an individual that possibly induces further noise on the RF-channel fluctuation [27].

Localisation can, however, also be achieved by device-free systems in which a subject is not equipped with a transmitter or receiver. Youssef et al. tracked a person by analysing moving average and variance of RSSI values from packets exchanged by WiFi nodes [41, 26]. It was then shown by Wilson, Kosba and others that the RSSI variance of a wireless signal can be used as indicator of motion of objects or subjects not equipped with a transmitter or receiver [10, 37].

The area in which environmental changes impact signal characteristics was considered by Zhang et al. [44]. They identified regions of 2 meters to 5 meters within which movement could be reliably detected [43]. In particular, they have been able to localise an object with an accuracy of 1 meters by creating hexagonal cell-clusters over which measurements are scheduled according to a TDMA scheme which was further improved by Wilson et al. in [37] to an average error of about 0.5 meters. The localisation of individuals was generalised by Lee et al. to five distinct environments [12]. The authors showed that the RSSI peak is concentrated in a vacant environment while it is spread and reduced in intensity in the presence of an individual. Lately, Patwari et al. discussed the simultaneous localisation of multiple individuals at the same time and presented a statistical model to approximate locations of individuals [16]. Zang et al. then solved this challenge by isolating the Line-of-Sight paths among two rows of wireless nodes from the differences in the received signal-strength on various frequency spectrums at distinct nodes [42]. With this approach, they have been able to simultaneously and continuously localise up to 5 persons in a changing environment with an accuracy of 1 meter. Following a different approach, Wagner et al. [35] consider an RFID-based radio tomography system for localisation of individuals. They introduce a novel transponder clustering approach to dramatically improve the time to find a first location which is then iteratively improved in accuracy. Another method, leveraging a passive system conditioned on ambient FM radio is presented by Popleteev in [18]. The author investigates the localisation performance of a single-receiver device-free localisation system, exploiting multiple channels from neighbouring FM radio stations. He could show a good accuracy in the distinction of five locations also considering same-day versus next-day performance. The accuracy deteriorated with fewer channels utilised and over the course of several days.

Only recently, the classification of activities and not only location was considered in the literature [24]. A detailed overview over most of these aspects is given by Scholz et al. in [23]. Most notably, in [17], Patwari et al. demonstrate that also the breathing rate of an individual can be detected by analysing the two-way RSSI of nodes that surround a subject. For some typical activities, Sigg, Shi and others demonstrated a good recognition accuracy for active and passive DFAR systems [30, 28, 21] in a single environment. For a passive, FM-based DFAR system it was also demonstrated how attention levels of individuals can be derived from the activities detected [29]. Scholz and others recently generalised these studies also to active RSSI-based systems [22]. Following a different approach, Hong et al. [7] investigate a recognition system with multiple antennas, utilising the signal subspace from Eigenvectors of the covariance matrix of an antenna array. The authors could detect locations and activities in an indoor environment with good accuracy and demonstrated that their method is superior to single-antenna systems in experimental case studies.

With an active, continuous-signal-based system, it was further demonstrated that activities conducted by multiple individuals can be detected simultaneously with good accuracy utilising multiple receive nodes and simple features and classifier systems [31].

The counting of subjects in the proximity of an RF-receiver is, for instance, investigated by [39, 14].

Recently, the recognition of gestures from continuous-signal-based systems was considered in [19, 4]. In particular, the authors leverage patterns of micro-Doppler fluctuations to identify complex movement patterns. In a related system, Adib and Katabi employ MIMO interference nulling and combine samples taken over time to achieve the same result while compensating for the missing spatial diversity in a single-antenna system [1]. We remark that the latter two systems require movement and gestures conducted towards or away from a receiver. Movement in other angles to the receiver will negatively impact the recognition capabilities.

While this work represents a broad range of studies on device-free activity-recognition, numerous questions remain

Feature	Description
FFT	average value after Fast Fourier transformation
ZCRe	Relation: $\left(\frac{\text{CHAN}}{\text{ZC}}\right)$
CM3	third central moment over values from one window
PEAK	count of signal peaks within 10% of the maximum
DIFF	mean difference between subsequent maxima
DMax	difference between subsequent maxima
CHAN	number of direction changes within one window
ZCDi	distance between zero crossings
ENER	normalised spectral energy over one window
ENTR	entropy of values within one sampling window
MAX	highest signal peak in one sampling window
MEAN	mean signal strength in one sampling window
MED	median signal strength in one sampling window
MIN	lowest signal peak in one sampling window
STD	standard deviation of the signal strength
VAR	variance of the signal's strength in one window
ZC	count of zero crossings

Table 1: Features considered for active RF-based DFAR

unsolved. This regards, for instance, the utilisation of multiple frequency ranges for the recognition, the detection while devices are carried and moved, the distinction between actual individuals and the identification of features and activity patterns that need not be retrained in new environments. Also, currently, the classification accuracy is not compared to traditional activity recognition systems.

This study advances the previous work by considering also movement speed, classification without re-training, and improved localisation and recognition accuracies. The latter is achieved by the consideration of new and additional features which are detailed in section 3. In addition, we compare the recognition accuracies of several active systems with a passive and an accelerometer-based recognition system.

3. FEATURES FOR RF-BASED AR

Activity recognition from RF-signal fluctuation exploits that received signal components are blocked and reflected by an object or entity in proximity so that a characteristic pattern might be induced on the observed evolution of a received signal. For objects in motion this signal fluctuation due to environmental effects such as moving cars, persons, trees as well as opened or closed doors, windows or moved furniture is generally referred to as slow fading.

We utilised a set of features and feature combinations frequently employed for activity recognition for the distinction of activities from fluctuation in the signal strength of a received RF-signal. The basic features utilised are detailed in table 1. Additionally, we combined each feature pair by first applying one feature over a window of two seconds of sampled values and the second feature over the set of values computed for these windows.

In order to find suitable features for a given scenario, we applied a feature subset selection process utilising a relief function with 20 neighbours and 50 reference examples. Additionally, we manually exploited various combinations of the resulting features in order to identify those which are most expressive for a set of classes to be distinguished.

Figure 1 discusses the features considered.

4. EXPERIMENTAL EVALUATION

We have conducted case studies in different environments to exploit RF-based DFAR for its various aspects. In particular, we distinguish between an *empty* environment and

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

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

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

Count of zero crossings

The count of zero crossings over a sample interval is a measure of the fluctuation in a received signal's strength.

It can be leveraged in order to estimate the count of individuals or movement in proximity of a receiver.

$$g(s_i) = \begin{cases} 0 & \text{if } \text{sgn}(s_{i-1}) = \text{sgn}(s_i) \\ 1 & \text{else} \end{cases}$$

$$\text{ZeroCross}(\mathcal{W}_t) = \sum_{s_i \in \mathcal{W}_t} g(s_i)$$

Distance between Zero Crossings

The distance between zero crossings defines, for periodic carrier signals, a base-line on the signal data against which other features can be normalised.

We denote the set of zero crossing samples

$$\overline{\mathcal{W}_t} = \{s_i | g(s_i) = 1\}$$

$$\text{distZeroCross}(\mathcal{W}_t) = \sum_{\substack{s_i, s_j \in \overline{\mathcal{W}_t}; \\ \nexists s_k \in \overline{\mathcal{W}_t} \text{ with } i<k<j}} \frac{j-i}{|\overline{\mathcal{W}_t}|}$$

Direction changes over a set of features within a sample window

The direction changes over a signal period indicates the noise or interference in a received signal

It can, in particular, be utilised in relation to the count of zero crossings in order to express how significantly a received signal envelope is impacted by environmental effects.

$$\overline{g}(s_i) = \begin{cases} 1 & \text{if } s_{i-1} < si \wedge s_i > s_{i+1} \\ 0 & \text{else} \end{cases}$$

$$\text{dirChan}(\mathcal{W}_t) = \sum_{s_i \in \mathcal{W}_t} \overline{g}(s_i)$$

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

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

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.

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

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

Mean difference between subsequent maxima

When the maximum peaks within a sample window are of similar magnitude, this indicates low activity in an environment or static activities. The opposite might be found with dynamic activities

$$\mathcal{W}_{\max}(\mathcal{W}_t) = \{s_i \mid s_i \in \mathcal{W}_t, s_{i-1} < s_i \wedge s_i > s_{i+1}\}$$

$$a(\mathcal{W}_t) = \sum_{\substack{\forall s_i, s_j \in \mathcal{W}_{\max}(\mathcal{W}_t); \\ i<j; \\ \nexists s_k \text{ with } i<k<j}} \frac{\mid s_i - s_j \mid}{\mid \mathcal{W}_{\max}(\mathcal{W}_t) \mid}$$

Figure 1: 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.

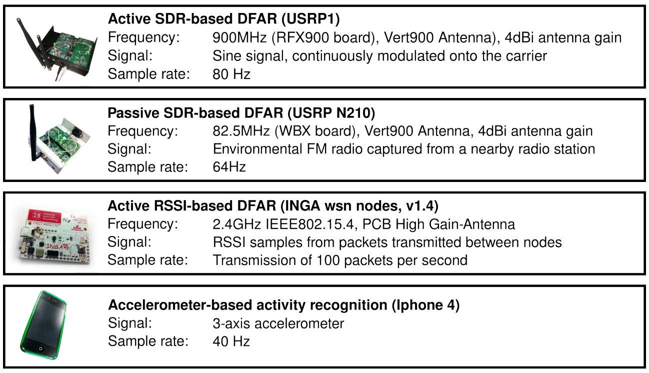


Figure 3: Configuration of the recognition hardware utilised

		USRP SDR nodes				INGA WSN nodes		
		Activity	Walking speed	Speed & location	Ad-hoc recogn.	Activity	Walking speed	Speed & location
Features	PEAK	**.159**	.01	**.163**	**.16**	–	–	–
	DIFF	**.141**	.007	**.161**	.117	**.065**	.013	.07
	MIN	.141	.005	.157	**.118**	.061	.013	.075
	MAX	.128	.001	.152	.105	.107	.024	**.128**
	ZC	**.089**	.011	**.121**	.073	–	–	–
	CM3-RMS	.088	0	.101	.094	**.022**	.003	.022
	STD	**.083**	.01	**.118**	**.072**	.051	.013	.053
	VAR	**.08**	**.009**	**.122**	.064	**.012**	.009	.014
	MAX-MIN	.079	**.009**	**.11**	.07	.014	**.05**	**.032**
	CM3-MEAN	**.078**	.004	**.117**	.061	**.024**	.025	.028
	MAX-MEAN	.078	.004	.117	.061	**.024**	.025	.028
	VAR-MEAN	.078	.004	.117	.061	**.024**	.025	.028
	CM3-MED	.074	**.006**	**.114**	**.061**	.022	**.095**	**.03**
	MED-MED	.074	**.006**	**.114**	.061	.022	.095	.03
	DMax	.063	-.004	.079	**.048**	–	–	–
	ZCrel	.032	**.016**	**.04**	.029	–	–	–
	MEAN	0	.005	-.004	-.004	**.072**	.016	**.096**

Table 2: Significance of features for various scenarios.

the activities *walking, crawling, lying* and *standing* as well as locations at which activities are conducted and walking speeds. Additionally, we considered various modifications of the system such as active and passive as well as continuous-signal- and RSSI-based systems, alternative environments as well as differing recognition hardware. For comparison, also an accelerometer-based recognition system is considered.

The indoor environments, populated with RF transmit and receive devices are depicted in figure 2. The seminar room (3m×5m) used is shown in figure 2a as well as the 1.8 meter wide corridor (figure 2b).

In both environments we consider the detection of the activities *walking, lying, standing, crawling* and the *empty* environment with active and passive USRP-based SDR (continuous signal) systems. In the seminar room, also an active RSSI-based system as well as the recognition by accelerometer devices are considered for comparison.

Apart from the comparison between recognition systems, we also consider the localisation of activities performed in the seminar room and the corridor and walking speeds in the seminar room. The configuration of the respective recognition hardware utilised is detailed in figure 3.

Since different activities are tracked in the environments illustrated in figure 2, we utilise varying sets of features for the activity recognition as detailed in table 2. We distinguished between the four cases *'recognition of activities'*, *'recognition of locations where activities are conducted'*, *'distinction of walking speeds'* and *'Ad-hoc recognition'*[1]. The table distinguishes between an USRP SDR-based system[2] [3] and an RSSI-based system for which we utilise the INGA sensor nodes[4]. The features selected for these systems differ due to the lower accuracy of the RSSI values and since some features did not make sense for RSSI values (marked in the table with '–'). Features were derived by applying the feature subset selection, which reduced the set of potentially relevant features to only 12 to 31 depending on the considered case. From the remaining set, we manually identified those with contradicting predictions and such reduced the overall feature set further. The features most suited (and in turn selected for the experimental evaluation) to classify the activities in each scenario are printed in bold in table 2.

Although there is a common set of best features that is prevalent for all cases, especially the features identified for the first case (mere recognition of activities) and the features identified for the distinction of walking speeds differ. This reflects the different nature of the two cases. While in the former case static and dynamic activities are mixed and the distinction between dynamic activities is rather course (only *walking* vs. *crawling*), in the latter case no static activities are considered but instead walking speed.

Furthermore, in the 3rd case that combines the detection of locations and walking speeds, a larger set of features was required to reach best results. This set is generally composed of the features identified for the first two cases.

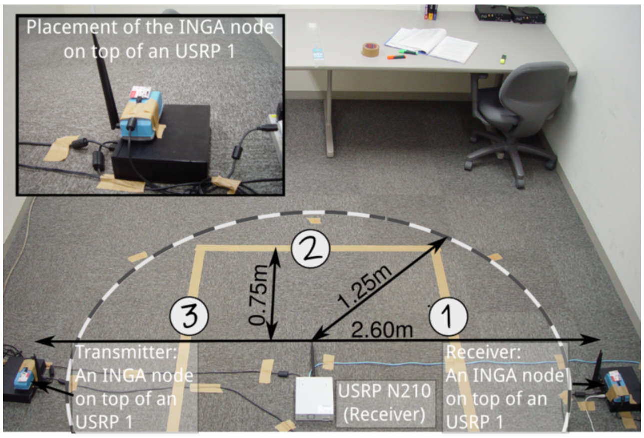
For the add-hoc recognition, we considered a generalisation to an alternative scenario where the classifier trained in one scenario was applied for classification in another scenario. Some new features have been identified to achieve a maximum classification accuracy in this case, but generally the features that have been successfully applied in the other three cases are most expressive also when we generalise to several scenarios. In summary, the features *PEAK*, *STD*, *VAR* and *CM3-MED* have shown good performance in many of the use cases considered. For an application designer, we believe that it is worth the effort to analyse a scenario for the activities that are expected to be conducted frequently in that scenario ahead of the selection of features and the design of the classification system since the optimum features for static and dynamic activities may significantly differ.

We investigate the performance of active and passive DFAR systems for various configurations and environmental situations. We mainly consider an active DFAR-based system with one transmit and one receive device but also compare the performance of this system to configurations with less capable and passive receivers. Finally, classification accuracies are compared to an accelerometer-based system.

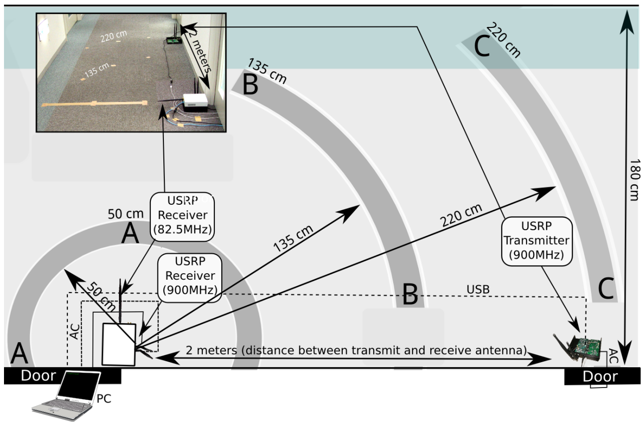
4.1 Active continuous-signal-based DFAR

For the active SDR-based DFAR system we utilised USRP 1 transmit and receive devices. A 2kHz sine signal, sampled at 320k and modulated onto a wireless carrier at 900MHz is continuously transmitted as detailed in figure 3. For the classification we utilise a Naive Bayes classifier with 100 sam-

[1] Recognition of activities in one environment when the training was conducted in another
[2] continuous signal
[3] http://www.ettus.com
[4] http://www.ibr.cs.tu-bs.de/projects/inga/



(a) Seminar room. USRP SDR (900 MHz) and WSN (RSSI) transmit and receive pairs are placed at opposite sides. A further USRP SDR in the center of the room captures FM-signals at 82.5 MHz. Additionally, subjects were equipped with accelerometer devices. Activities are performed at the locations marked 1,2,3 and on the circle indicated



(b) Corridor. USRP SDR transmit and receive devices (900 MHz) are placed alongside a wall in a corridor in 2 meters distance. Additionally, a USRP SDR receiver on top of the 900 MHz receiver captures environmental FM-signals at 82.5 MHz. Activities are performed at the areas marked A, B, and C in 0.5m, 1.35m and 2.2m distance to the receiver

Figure 2: Indoor scenarios in which the case studies with active and passive DFAR systems were conducted

ple points and a Loess window of 0.5, a Classification tree[5] with two or more instances at its leaves and a k-NN classifier with $k = 10$. Results are presented after 10-fold cross validation.

4.1.1 *Distinction between five basic activity classes*

First, we distinguish between the basic classes *walking, crawling, lying, standing* and the *empty* environment in the scenario depicted in figure 2a. With these classes, it is possible to detect simple situations in indoor scenarios. For instance, we might detect presence of non-cooperating intruders, activities conducted by persons in emergency situations or the status of indoor environments for maintenance or surveillance. In this study we consider the detection of activity from a single subject. We utilise the features marked bold in the row *'USRP SDR nodes – Activity'* of table 2.

Three subjects (one at a time) have conducted the five activities for 2 minutes each. Features were generated from sample windows of two seconds. The static activities *standing* and *lying* were conducted at the locations labelled '1', '2' and '3' while the dynamic activities *walking* and *crawling* were performed along the circle indicated in the figure. Table 3 depicts the classification accuracies reached for the k-NN classifier. Table fields with entries of 0.0 are omitted for readability.

We observe that the distinction between these five general activities is well feasible. In our experiments, the k-NN classifier generally performed slightly better but comparable to the other two classifiers. We therefore omit a detailed discussion on the results from the Bayes and classification tree algorithms. Table 4 shows the overall classification accuracy (CA) for all classifiers together with their information score (IS), Brier score and the area under the ROC[6] curve (AUC) as defined by [9, 33]. 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 outcome. The AUC equals the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one.

Gr. truth	Classification: crawling	empty	lying	standing	walking	recall
crawling	**.769**			.019	.212	.769
empty		**.901**	.018	.081		.901
lying	.006	.064	**.815**	.115		.815
standing		.042	.12	**.825**	.012	.825
walking	.031	.006		.006	**.956**	.956
precision	.870	.847	.853	.825	.921	

Table 3: Confusion matrix for the classification of five basic activities by the k-NN classifier

Learner	CA	IS	Brier	AUC
Naive Bayes	0.708	1.42	0.413	0.958
Classification tree	0.786	1.65	0.428	0.921
k-NN	0.864	1.792	0.226	0.980

Table 4: Performance of the three classifiers for the distinction between five basic activity classes

4.1.2 *Distinction of different locations*

In some scenarios, for instance in surveillance cases or for property maintenance, a localisation of activities conducted is anticipated. We demonstrate the localisation of activities performed with the same feature set as for the above study. The static activities 'standing' and 'lying' have been conducted by all subjects at three distinct locations. Clearly, the reflections of the radio waves might differ dependent on the location at which these activities were conducted.

[5] We used the implementation of the Tree learner in the Orange data mining toolkit (http://orange.biolab.si/)
[6] Receiver Operating Characteristic

Ground truth \ Classification	cr	em	ly1	ly2	ly3	st1	st2	st3	wa	rec
cr	**.75**						.019		.231	.750
em		**.892**	.009		.009		.054	.036		.892
ly@1	.018	.055	**.691**		.091	.018		.127		.691
ly@2				**1.0**						1.0
ly@3		.157	.176		**.451**	.216				.451
st@1			.037		.167	**.685**	.056	.056		.685
st@2	.018	.109				.091	**.691**	.073	.018	.691
st@3		.035	.123			.035	.105	**.684**	.018	.684
wa	.038	.006					.006		**.95**	.950
prec	.830	.832	.667	1.0	.605	.661	.691	.684	.915	

Table 5: Classification accuracy for the k-NN classifier for the distinction between activities and their location

Learner	CA	IS	Brier	AUC
Naive Bayes	0.656	1.888	0.500	0.973
Classification tree	0.710	2.036	0.580	0.923
k-NN	0.799	2.372	0.301	0.984

Table 6: Performance of the classifiers for the distinction between locations at which activities are conducted

Therefore, a localisation of these activities might be feasible based on RF-channel-based features. Table 5 depicts our results for the k-NN classifier.

In the table, we distinguish between the empty room, a subject crawling or walking and additionally whether she is lying or standing at one of the locations 1, 2 or 3 (cf. figure 2a). With the increased set of activities, the accuracy drops for the activities crawling and walking and for the empty room. For lying, the detection accuracy reaches 1.0 when the subject is located at location 2 while locations 1 and 3 are confused in some cases. Standing is detected about equally well for all three locations. Summarising, although the classification accuracy drops for most activities, due to the increased number of distinct cases, the results also suggest that an indication on a likely location at which an activity is conducted can be provided by RF-based activity recognition together with a prediction of the activity. Table 6 shows the overall classification accuracy and the IS, Brier and AUC scores for all classifiers.

4.1.3 Distinction of walking speeds

Another interesting aspect is the speed at which dynamic activities are performed in order to classify the haste or stress level of monitored subjects. We attempt to distinguish different walking speeds but abstract at first from all other activities. All subjects have been walking continuously on the circle indicated in figure 2a with three different walking speeds. The individuals have approximately conducted the experiments with 0.5 meters per second (m/s), 1 m/s and 2 m/s. The walking speed was controlled by the subjects autonomously. In order to support an accurate estimation of walking speed, subjects were equipped with a digital stopwatch counting seconds. Additionally, we marked the circle with tape in a distance of 1 meter each so that subjects could control their walking speed.

We used the features marked bold in the column *'USRP SDR nodes – Walking speed'* of table 2 for this scenario. We observe that the scored by the features in this case is generally worse than in the previous cases. Furthermore, the set of most suitable features greatly differs. Classification results for the k-NN classifier are depicted in table 7.

Truth \ Classification	0.5 m/s	1 m/s	2 m/s	recall
0.5 m/s	**.585**	.226	.189	.585
1 m/s	.111	**.667**	.222	.667
2 m/s	.143	.286	**.571**	.571
precision	.775	.522	.526	

Table 7: Accuracy for the k-NN classifier on the walking speed of individuals in the scenario depicted in figure 2a

	.5m/s	1m/s	2m/s	cr	em	ly1	ly2	ly3	st1	st2	st3	rec
.5m/s	**.642**	.208	.094	.057								.64
1m/s	.25	**.611**	.028	.111								.61
2m/s	.278	.056	**.444**	.222								.44
cr		.115	.058	**.769**						.019	.038	.77
em					**.874**	.009		.009		.09	.018	.87
ly@1					.091	**.691**		.073	.018		.127	.69
ly@2							**1.0**					1.0
ly@3					.157	.176		**.471**	.196			.47
st@1						.037		.167	**.685**	.093	.019	.69
st@2		.018			.127				.109	**.727**	.018	.73
st@3	.018			.018	.035	.158			.053	.053	**.667**	.67
prec	.694	.537	.471	.769	.815	.644	1.0	.632	.649	.678	.745	

Table 8: Joint classification of walking speed and location

For the distinction of walking speeds the classification accuracy is lower than for the static cases above. Although the classifier is able to give an indication of the actual walking speed, the absolute accuracy never reaches 0.7. We conclude that it is hard for a continuous signal-based system to accurately distinguish cases as fine grained as the speed of an individual. However, an indication whether a person is in a haste or not is clearly possible.

4.1.4 Joint distinction of walking speed and location

In a practical application, various of the activity classes discussed above are of interest. For instance, in order to understand the situation of people passing by some interactive displays in a corridor or passage, we are in the first place interested whether a person is present in the corridor or not (and switch off the display to save energy in the latter case). Then, if a person is actually present, we are interested, whether she is standing and in front of which display or, if not, whether she is walking in a haste or relaxed so that the message displayed can be adapted to her assumed attention status. While it is of course feasible to design a multi-staged recognition system to obtain this information [28], it is also possible to reach acceptable results in an integrated one-staged recognition [29].

Combining both previous cases, we attempt to distinguish in one step not only between walking speeds but also between locations at which activities are conducted. This means that we distinguish between 11 classes simultaneously. We utilise an optimised set of features in order to achieve best classification performance (cf. column *'USRP SDR nodes – Speed & location'* of table 2). In total, a set of 12 features is utilised in this scenario to distinguish between the 11 classes. The classification accuracy reached is depicted in table 8 for the k-NN classifier.

It drops due to the high count of different classes but still an indication which activity is conducted is possible. Furthermore, we observe from the table that the confusion among the classes is mainly within the static or dynamic classes but not across them. None of the dynamic classes

Learner	CA	IS	Brier	AUC
Naive Bayes	0.356	1.327	0.941	0.968
Classification tree	0.636	2.031	0.728	0.896
k-NN	0.723	2.483	0.391	0.982

Table 9: Performance of the classifiers for the distinction of locations of activities and walking speeds

Ground truth \ Classification	crawling	empty	lying	standing	walking	recall
crawling	**.713**	.02	.01	.02	.238	.713
empty		**.967**	.033			.967
lying	.01	.186	**.706**	.098		.706
standing	.111	.324	.306	**.241**	.019	.241
walking	.284	.028	.009		**.679**	.679
precision	.621	.599	.655	.684	.740	

Table 10: Classification accuracy for the k-NN classifier without prior training in the environment considered.

(*walking* or *crawling*) is mistaken for a static one and only few static classes are mistaken for dynamic classes. Table 9 shows the overall classification accuracy and the IS, Brier and AUC scores for all classifiers.

4.1.5 *Generalisation to other environments*

Practical applications of a recognition system might require that the system is applicable in a novel scenario ad-hoc with a pre-trained classifier. In particular, in an IoT in which sensing devices might be frequently relocated, prior training for each placement is not feasible. Therefore, we are interested in the generalisation of features to different scenarios. Previously, the classifiers have been trained for a single scenario only. The same, trained classifier will not likely reach an equally high classification accuracy in a completely different setting. We therefore performed another case study in the setting depicted in figure 2b. This alternative scenario is conducted in a corridor. The distances in which the recognition hardware is deployed and their relative distance to the locations at which activities are performed in this scenario are comparable to those utilised in the previous studies. In particular, location 1 in the seminar room and location A in the corridor are both 50 cm apart from the receiver. Similarly, location 3 and location C are both about 2 m apart from the receiver (2 m and 2,2 m distance respectively). The classifiers were in this study trained in one scenario while classification was conducted in the alternative one. The features utilised are detailed in column *'USRP SDR nodes – Ad-hoc recognition'* of table 2.

Classification results for the k-NN classifier are depicted in table 10.

The overall classification accuracy of the k-NN classifier drops but it is still above 0.7 for most cases. Worst classification results are reached for the standing case. Since this static activity mainly relies on the static change in the signal strength, the changed environment had great impact on the classification accuracy.

4.2 Active RSSI-based DFAR

Contemporary wireless consumer devices are seldom capable of accessing the RF-channel directly but rather at the packet level. Consequently, the information available on activities conducted in the environment is, for instance, the Link Quality Indicator (LQI), the Received Signal Strength

Ground truth \ Classification	crawling	empty	lying	standing	walking	recall
crawling	**.561**	.01			.429	.561
empty		**.776**	.098	.127		.776
lying		.086	**.867**	.047		.867
standing		.131	.074	**.788**	.007	.788
walking	.04				**.960**	.960
precision	.821	.726	.844	.854	.867	

Table 11: Classification accuracy achieved by the k-NN classifier for the activities walking, crawling, standing, lying and the empty room from fluctuation in the RSSI values

Classification	cr	em	ly1	ly2	ly3	st1	st2	st3	wa	recall
cr	**.582**	.01							.408	.582
em		**.771**		.102		.024	.049	.054		.771
ly@1			**.735**		.194	.02		.051		.735
ly@2		.414		**.466**		.052	.069			.466
ly@3			.182		**.747**	.01		.061		.747
st@1		.122		.061	.024	**.512**	.11	.171		.512
st@2	.011	.118		.065		.14	**.43**	.226	.011	.430
st@3		.185	.056	.019	.056	.139	.139	**.398**	.009	.398
wa	.05								**.95**	.950
prec	.781	.705	.750	.443	.733	.519	.513	.430	.871	

Table 12: Classification accuracies using the k-NN classifier for the distinction of locations of activities

Indicator (RSSI) or the Signal-to-Noise-Ratio (SNR). since this information is provided at packet level only, the sampling frequency is then restricted by the rate at which packets are received. Furthermore, the accuracy of these values is usually low. Therefore, we expect a lower classification accuracy for RSSI-based DFAR. We utilised INGA wireless sensor nodes in the scenario depicted in figure 2a. The two nodes have been placed on top of the USRP 1 devices and were programmed to continuously transmit and receive packets. The transmit node sent 100 packets per second which were then received and analysed for their Link Quality Indicator (LQI) and Received Signal Strength Indicator (RSSI) from the receiver. Since in our case the LQI was not decisive to distinguish between various activities, we omitted this information and based the classification on the RSSI only. For the INGA nodes, the RSSI is an integer value. In our case, we experienced values in the range from 12 to 60 with a median of 48 over about 500000 samples.

The features we utilised from the sampled RSSI values are depicted in table 2. For the distinction of basic activities, we utilised the feature set printed bold in the column *'INGA wsn nodes – Activity'* of table 2. Table 11 details the classification accuracies achieved for the k-NN classifier.

We observe that the accuracy is lower than for the continuous signal-based recognition due to the lower accuracy of the RSSI samples. With the same set of features, we also attempted to localise activities based on RSSI information. Table 12 depicts the classification accuracies for this case with the k-NN classifier.

While the classification accuracy drops compared to continuous signal-based systems, the classification still provides a good indication towards the correct activity conducted. To distinguish the walking speed, we achieved best results by utilising only two features as depicted in column *'INGA WSN nodes – Walking speed'* of table 2. The classification accuracy for the k-NN classifier is detailed in table 13.

G. truth	Classification .5 m/s	1 m/s	2 m/s	recall
.5 m/s	**.775**	.186	.039	.775
1 m/s	.186	**.598**	.216	.598
2 m/s	.04	.16	**.8**	.800
precision	.782	.624	.762	

Table 13: Classification accuracy utilising the k-NN classifier to classify walking speeds from RSSI samples

	Classification .5m/s	1m/s	2m/s	cr	em	ly1	ly2	ly3	st1	st2	st3	rec
.5m/s	**.539**	.235	.029	.186							.01	.54
1m/s	.196	**.588**	.144	.062					.01			.59
2m/s	.01	.14	**.84**	.01								.84
cr	.214	.112	.051	**.571**	.01				.01	.01	.02	.57
em					**.761**		.122		.015	.039	.063	.76
ly@1						**.827**		.133	.02		.020	.83
ly@2					.414		**.483**		.017	.069	.017	.48
ly@3						.192		**.737**	.01		.061	.74
st@1	.012				.159		.037	.024	**.524**	.049	.195	.52
st@2	.032			.022	.129		.086		.14	**.376**	.215	.38
st@3	.009			.028	.148	.056	.028	.065	.185	.111	**.37**	.37
prec	.545	.538	.792	.644	.703	.764	.418	.768	.506	.547	.396	

Table 14: Classification accuracy utilising the k-NN classifier for the distinction of activities, their location and walking speeds based on RSSI information

Finally and summarising these results, classifications considering all locations and velocities considered separately are depicted in table 14.

Here, we utilised the features printed bold in column *'INGA WSN nodes – Speed & location'* of table 2. Similar to the active SDR case, we observe that static and dynamic activities are only seldom confused. The main errors are attributable to confusions within the set of static or within the set of dynamic activities. Again, classification accuracy is lower than for the continuous signal-based system but still a good indication towards the right class (activity and location) is given.

4.3 Activity detection from passive SDR

Passive DFAR systems don't utilise a dedicated transmitter as part of the recognition system. Instead, environmental signals such as GSM, UMTS, FM, WiFi are exploited. Clearly, this eases the installation of such systems in an environment. However, since the signal utilised for detection is not under the control of the classification system, we expect a reduced classification performance. In the scenario depicted in figure 2a, we deployed an USRP N210 SDR device (cf. figure 3 in the center of the room and sampled the signal evolution at 82.5 MHz, the frequency of a nearby FM-radio station. The features we utilised were the mean, variance, normalised spectral energy and the entropy. The classification results are detailed in table 15. We conclude that with passive continuous signal-based DFAR a lower but still reasonable classification accuracy is possible.

4.4 Activity detection via accelerometer data

Activity recognition is most prominently performed with data from accelerometer devices. These devices are often attached to a person or are at least incorporated by a device carried by the person. While the classification accuracy achieved with accelerometer devices is typically high, the subjects monitored therefore have to cooperate (at minimum, wear the devices).

Ground truth	Classification empty	lying	standing	walking	crawling
empty	**.739**	.087	.145	.029	
lying		**.733**	.213	.027	.027
standing		.157	**.843**		
walking		.083	.012	**.706**	.2
crawling		.054		.230	**.716**

Table 15: Mean accuracy for FM-based passive DFAR for the activities *lying, standing, crawling, walking* and *empty*

We compare the classification accuracy achieved with accelerometer devices in the scenario depicted in figure 2a to the classification accuracy achieved with the three DFAR systems considered for the activities *walking, crawling, standing, lying.* We utilised an off-the-shelf accelerometer shipped with an iPhone 4 smartphone. We did not calibrate the accelerometer or fix it at any specific body part but placed the phone in upright position in the right front pocket of the trousers the subjects were wearing. The accelerometer samples (at 40 Hz) were taken simultaneously to the DFAR experiments described above. Since the accelerometer is not capable of detecting the empty room, this class was omitted when calculating the accuracy for the DFAR system. Table 16 depicts the classification accuracies reached. We observed that the classification accuracy achieved, especially for the active continuous signal-based DFAR is close and comparable to the accelerometer case.

While the accelerometer-based recognition could probably be further improved by putting greater effort on the calibration and accurate placement, note that also the DFAR results can be improved by adding further receive devices as described above.

5. CONCLUSION

We have investigated the classification of activities from environmental RF-signals. In particular, we exploited the fluctuation in the time evolution of the strength of a received signal due to movement and activities of individuals in proximity. For active continuous signal-based DFAR we demonstrated in various case studies in three indoor environments the distinction between five basic activities, their simultaneous localisation within these environments as well as walking speeds and the generalisation to ad-hoc DFAR in which no prior training is required in a novel environment. Additionally, we exploited the detection of activities from multiple subjects at one time as well as the impact of an increased number of receive devices.

Since active continuous signal-based DFAR is potentially the easiest case for RF-based DFAR, we also considered an active RSSI-based DFAR system for the same scenarios as well as passive continuous signal-based DFAR.

Finally, the accuracy achieved by these DFAR systems was compared to the accuracy achieved with accelerometer devices attached to subjects performing the activities.

We could show that RF-based DFAR can reach results comparable to accelerometer-based activity recognition while is is less obtrusive for monitored subjects and, compared to video-based systems, more privacy preserving. RF-based DFAR can well be integrated in smart spaces created by the upcoming Internet of Things since virtually all IoT devices will incorporate an interface to the RF-channel.

Gr. truth	ly	st	wa	cr
lying	**.976**	.024		
standing		**1.0**		
walking			**.955**	.045
crawling			.253	**.748**

(a) Classification accuracy for accelerometer-based activity recognition by a k-NN

Gr. truth	ly	st	wa	cr
lying	**.904**	.096		
standing	.096	**.898**	.006	
walking		.013	**.962**	.025
crawling		.038	.212	**.75**

(b) Accuracy for active continuous signal-based DFAR by a k-NN algorithm

Gr. truth	ly	st	wa	cr
lying	**.882**	.118		
standing	.12	**.869**	.007	.004
walking			**.953**	.047
crawling		.01	.439	**.551**

(c) Classification accuracy for active RSSI-based DFAR by a k-NN algorithm

Gr. truth	ly	st	wa	cr
lying	**1.0**			
standing	.056	**.98**	.022	
walking	.023		**.874**	.102
crawling	.044		.144	**.811**

(d) Accuracy for passive continuous signal-based DFAR by a k-NN algorithm

Table 16: Confusion matrices for accelerometer-based and RF-based device-free activity recognition systems

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