RF-Sensing of Activities from Non-Cooperative Subjects in Device-Free Recognition Systems Using Ambient and Local Signals

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Abstract—We consider the detection of activities from non-cooperating individuals with features obtained on the radio frequency channel. Since environmental changes impact the transmission channel between devices, the detection of this alteration can be used to classify environmental situations. We identify relevant features to detect activities of non-actively transmitting subjects. In particular, we distinguish with high accuracy an empty environment or a walking, lying, crawling or standing person, in case-studies of an active, device-free activity recognition system with software defined radios. We distinguish between two cases in which the transmitter is either under the control of the system or ambient. For activity detection the application of one-stage and two-stage classifiers is considered. Apart from the discrimination of the above activities, we can show that a detected activity can also be localized simultaneously within an area of less than 1 meter radius.

Index Terms—Pervasive computing, signal analysis, synthesis, and processing, signal processing, location-dependent and sensitive

1 Introduction

In the approaching Internet of Things (IoT), virtually all entities in our environment will be enhanced by sensing, communication and computational capabilities [1], [2]. These entities will provide information on environmental situations, interact in the computation and processing of data [3] and store information. In order to sense environmental situations, common sensors in current applications are light, movement, pressure, audio or temperature [4]. Clearly, for reasons of cost and sensor size it is desired to minimise the count of distinct sensors in IoT entities. The one sensor class that defines the minimum set naturally available in virtually all IoT devices is the radio frequency (RF)-transceiver to communicate with other wireless entities. It is also shipped with nearly every contemporary electronic device like mobile phones, notebooks, media players, printers as well as keyboards, mouses, watches, shoes and rumour has spread about even media cups. Therefore, the RF transceiver is a ubiquitously available sensor class. It is capable of sensing changes or fluctuation in a received RF-signal. Radio waves are blocked, reflected or scattered at objects. At a receiver, the signal components from distinct signal paths add up to form a superimposition. When objects that block or reflect the signal path of some of these signal components are moved, this is reflected in the superimposition of signal waves at the receiver. We assert that specific activities in the proximity of a receiver generate characteristic patterns in the received superimposed RF-signal. By identifying and interpreting these patterns, it is possible to detect activities of non-cooperating subjects in an RF-receiver's proximity.

Although the wireless channel is occasionally utilised for location detection of other RF devices [5], [6] or passive entities [7], [8], it is seldom used to detect other contexts like activities from entities which are not equipped with a RF-transceiver.

We consider the detection of activities of device-free entities from the analysis of RF-channel fluctuations induced by these very activities. In analogy to the definition of device-free radio-based localisation systems (DFL) [7] we define device-free radio-based activity recognition systems (DFAR) as *systems which recognise the activity of a person using analysis of radio signals while the person itself is not required to carry a wireless device* (cf. [9]). In addition to the sensor type employed, we further categorise radio-based activity recognition systems by the parameters enlisted in Table 1. In particular, we distinguish between passive and active systems depending on whether a transmitter is part of and under control of the radio-based recognition system. Also, an ad-hoc system can be installed in a new environment without re-training the classifier, while a non-ad-hoc system requires initial training or configuration.

In this work, we focus on the detection of static and dynamic activities of single individuals by active and passive, non-ad-hoc DFAR systems. The active system employs a dedicated transmitter as part of the recognition hardware

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Manuscript received 27 Jan. 2012; revised 10 Oct. 2012; accepted 14 Feb. 2013; date of publication 20 Feb. 2013; date of current version 3 Mar. 2014. For information on obtaining reprints of this article, please send e-mail to: reprints@ieee.org, and reference the Digital Object Identifier below. Digital Object Identifier no. 10.1109/TMC.2013.28

TABLE 1
Classification-Parameters for Radio-Based Context Recognition Systems

Parameter	Values
Sensor type	Device-bound; Device-free
Sensing modality	Passive; Active
Setup	Ad-hoc; Non-ad-hoc (requires training)

while the passive system utilises solely ambient FM radio from a transmitter not under the control of the system. Compared to preliminary work on RF-based activity recognition [10], [11], [12], [13], [14], the novel contributions are

1. A comprehensive discussion of research campaigns utilising RF-channel based features for the detection of location or activities (Section 2)
2. A concise investigation on possible features for RF-based activity recognition (Section 4)
3. A case study on activity classification of a single individual from RF-channel based features for
   a. an active DFAR system utilising 900 MHz software defined radio nodes (Section 5.1), and
   b. a passive DFAR system utilising ambient FM radio signals at 82.5 MHz (Section 5.2) considering in both cases
4. the classification accuracy with respect to activity and location.

The majority of the features we consider are amplitude-based. Since with the received signal strength indicator (RSSI), a related value is commonly provided by contemporary transceiver hardware, the features utilised in this study can be implemented similarly for most current mobile devices.

Our discussion is structured as follows. In Section 2 we review the related work on activity and location recognition with a particular focus on radio frequency based or related environmental features. Section 3 then discusses use-cases and application scenarios for RF-based activity recognition. The features utilised in our case-studies are introduced, analysed and discussed in Section 4. Based on some of these features, we report from the experiments in Section 5. In particular, we demonstrate the detection of five activities with active and passive DFAR systems. We can also show that a localisation of these activities is feasible simultaneously from the same set of features. Section 6 summarises the results and closes our discussion.

2 Related Work

Activity recognition comprises the challenge to recognise human activities from the input of sensor data. A broad range of sensors can be applied for this task. Traditionally, accelerometer devices have evolved as the standard equipment for activity recognition both for their high diffusion and convincing recognition rates [15], [16]. General research challenges for activity recognition regard the accurate classification of noisy data captured under real world conditions [18] or the automation of recognition systems [19]. Another problem that is addressed in depth only recently is the creation of classification systems that scale to a large user base. With increasing penetration of sensor enriched environments and devices, the diversity in user population poses new challenges to activity recognition. Abdullah et al. for instance address this challenge by maintaining several groups of similar users during training to identify inter-user differences without the need for individual classifiers [20].

Even more fundamental and aligned to this scaling problem is the required cost for accurately equipping subjects, training them to the system, equipping the environment or the users and most importantly, having them to actually wear the sensing hardware. The classification accuracy is highly dependent on the accurate sensor location. The integration of sensors in clothing as well as the recent remarkable progress in the robustness to rotation or displacement have improved this situation greatly [21]. However, a subject is still required to cooperate and at least wear the sensors [22]. This requirement cannot be assured generally in real-world applications. In particular, even devices as private as mobile phones, which are frequently assumed to be constantly in the same context as its owner [23], [24], [25], cannot serve as a sensor platform suitable to accurately capture the context of an individual. Dey et al. investigated in [26] that users have their mobile phone within arms reach only 54 percent of the time. This confirms a similar investigation of Patel et al. in 2006 [27] which reported a share of 58 percent for the same measure.

These general challenges of activity recognition can be overcome be using an environmental sensing modality. Naturally, vision-based approaches, such as video [28] and recently also the Kinect and wii concepts have been employed by scientists to classify gestures and activities [29]. However, the burden of installation and cost make such approaches hard to deploy at scale [22]. Recently, researchers therefore explore alternative sensing modalities that are pre-installed and readily available in environments and therefore minimise installation cost.

Patel et. al. coined the term infrastructure-mediated sensing and demonstrated in 2007 that alterations in resistance and inductive electrical load in a residential power supply system due to human interaction can be automatically identified [30]. They leveraged transients generated by mechanically switched motor loads to detect and classify such human interaction from electrical events. In a related work from 2010, Gupta et al. analysed electromagnetic interference (EMI) from switch mode power supplies [31]. In [32] they showed that it is even possible to detect simple gestures near compact fluorescent light by analysing the EMI-structures, effectively turning common light bulbs in a house into sensors. Environmental sensing with atypical sensing devices is also considered by Campbell et al. and Thomaz et al. who present an activity detection method utilising residential water pipes [33], [34]. In [35], Cohn et al. form a residual Power-line system into a large distributed antenna to sense low power signals from parasitic or distant devices. These approaches all require explicit interaction between a cooperating individual and a specific sensing entity. These approaches are bound to specific environments or installations and typically are only feasible indoors. An infrastructure mediated sensing medium with greater range is the RF-channel. Signal strength, amplitude fluctuation or noise level provide information that can be utilised to classify environmental situations.

Several authors considered the localisation of individuals based on measurements from the RF-sensor. Results are typically achieved by analysing the RF-signal amplitude, namely the RSSI of a received signal. Classical approaches are device-bound and utilise the RF-sensor for location estimation of an active entity equipped with a RF transceiver. In these approaches, the impact of multi-path fading and shadowing on the transmission channel and therefore the strength of an RF signal is exploited. These approaches were driven by the attempt to provide capabilities of indoor localisation. The first promising work was the RADAR system presented by Bahl et al. [36]. The authors took advantage of existing communications infrastructure, Wi-Fi access points, and employed RSSI fingerprints to identify locations off-line. With location, this approach was then applied also with GSM networks [37], [38], FM radio signals [39], [40] and domestic powerline [27], [41]. Recently, automations have been proposed for such fingerprinting approaches [42], [43].

While these systems rely on a two staged approach in which first a map of fingerprints is created off-line, recent work achieves on-line real-time localisation of entities equipped with a wireless transceiver based on Wi-Fi or FM radio [44], [45], [46]. These studies were initiated in 2006 by Woyach et al. who detail various environmental changes and their effect on a transmit signal [5]. The authors utilise MICAz nodes to show that motion detection based on RSSI measurements can be more accurate than accelerometer data when changes are below the sensitivity of the accelerometer. They experimentally employ several indoor-settings in which a receive node analyses a signal obtained from a transmitter. In this study they focused on an increased fluctuation in the RSSI signal level. Additionally, the authors showed that velocity of an entity can be estimated by analysing the RSSI pattern of continuously transmitted packets of a moving node. This work was advanced by Muthukrishnan et al. who study in 2007 the feasibility of motion sensing in a Wi-Fi network [6]. They analyse fluctuation in the 1 byte 802.11 RSSI indicator to sense whether a device is moving. The authors consider only the two cases of motion and no motion and achieve a classification accuracy of up to 0.94. A more fine grained distinction was made by Anderson and Muller and Sohn et al. based on fluctuations in GSM signal strength [47], [48]. The authors of [47] implement a neural network to detect the travel mode of a mobile phone. They monitor the signal strength fluctuation from cells in the active set to distinguish between walking, driving and stationary with an accuracy between 0.8 and 0.9.

Sohn et. al describe a system that extracts seven features from GSM signal strength measurements to distinguish six velocity levels with an accuracy of 0.85 [48]. The features mainly build on distinct measures of variation in signal strength and the frequency of cell-tower changes in the active set.

While all previously mentioned results considered special installations of the wireless transmitters, Sen et al. presented a system that allows the localisation of a wireless device with an accuracy of about 1 meter from Wi-Fi physical layer information even when the receiver is carried by a person that might induce additional noise to the captured features [49].

Summarising, these studies are examples of device-bound and active velocity and location estimation approaches since they require that the located entity is equipped with a RF transceiver.

Recently, some authors also consider RF-sensing to detect the presence or location of passive entities. Since these systems require at least one active transmitter, they can be classified as active, device-free systems.

Youssef defines this approach as device-free localisation (DFL) in [7] to localise or track a person using RF-Signals while the entity monitored is not required to carry an active transmitter or receiver. They localised individuals by exchanging packets between 802.11b nodes in corners of a room and analysed the moving average and its variance of the RSSI [7]. Classification accuracy reached up to 1.0 for some configurations. Additionally, they presented a fingerprint-based localisation system with an accuracy of 0.9. Later, they improved their approach using less nodes [8]. A passive radio map was constructed offline before a Bayesian-based inference algorithm estimated the most probable location. These experiments have been conducted under Line-of-Sight (LoS) conditions. Also, Wilson and Patwari showed in conformance with the findings of Kosba et al. [50] that the variance of the RSSI can be used as an indicator of motion of non-actively transmitting individuals regardless of the average path loss that occurs due to dense walls and stationary objects [51]. The area in which environmental changes impact signal characteristics was then considered by Zhang et al. They used 870 MHz nodes arranged in a grid to show that for each link an elliptical area of about 0.5 to 1 meters diameter exists for which RSSI fluctuation caused by an object traversing this area exceeds measurements in a static environment [52]. They identified a valid region for detecting the impact (i.e., the RSSI fluctuations exceeding the measured threshold in a static environment) for transceiver distances from 2 m to 5 m for the considered 870 MHz frequency range [53]. By dividing a room into hexagonal cell-clusters with measurements following a TDMA scheduling, an object position could be derived with an accuracy of around 1 meter. This accuracy was further improved by Wilson and Patwari in 2011 [51]. They utilised a dense node array to locate individuals within a room with an average error of about 0.5 meters. This was possible by instrumenting a tomographic image over the two-way RSSI fluctuations of nodes [54]. All these studies consider a single experimental setting.

In a related work, Lee et al. sense the presence of an individual in five distinct environments [55]. They showed that the RSSI peak is concentrated in a restricted frequency band in a vacant environment while it is spread and reduced in intensity in the presence of an individual. In 2011, Kosba et al. presented a new system for the detection of human movement in a monitored area [50]. Using anomaly detection methods they achieved 6 percent miss detection and a 9 percent false alarm rate when utilising the mean and standard deviation of the RSSI in two environments. They further implemented techniques to counteract effects of dispersion. This was accomplished by continuously adding newly measured data which did not trigger the detection. The previous results all considered the localisation of a single individual.

The simultaneous localisation of multiple individuals at the same time was first mentioned and studied by Patwari and Wilson in [56]. The authors derive a statistical model to approximate the position of a person based on RSSI variance which can be extended to multiple persons. This aspect together with the previously untackled problem that environmental changes over time might necessitate frequent calibration of the location system was approached by Zhang et al. [57]. The authors isolate the LoS path by extracting phase information from the differences in the RSS on various frequency spectrums at distributed nodes. Their experimental system is with this approach able to simultaneously and continuously localise up to five persons in a changing environment with an accuracy of 1 meter.

We summarise that most work conducted in the area of RF-based classification with passive participants is related to the localisation of individuals. The feasibility of this approach was verified in various environmental settings and at various frequencies. The features utilised are mostly the RSSI, its moving average, mean or RSSI fingerprint. Also, two-way RSSI variance was employed. With these features a localisation accuracy of about 0.5 meters was possible or the simultaneous localisation of up to five persons in a changing environment with an accuracy of 1 meter.

While the localisation of individuals based on features from the radio channel can therefore generally be considered as solved, recently, some authors considered active DFAR approaches to also detect activities.

Patwari et al. monitor breathing based on RSS analysis [58]. The monitored area was surrounded by twenty 2.4 GHz nodes and the two-way RSSI was measured. Using a maximum likelihood estimator they approximated the breathing rate within 0.1 to 0.4 beats accuracy.

Recently, we also conducted preliminary studies regarding the use of features from a RF-transceiver to classify static environmental changes such as opened or closed doors, presence, location and count of persons with an accuracy of 0.6 to 0.7 [12], [13], [14], [59]. We utilised USRP Software defined radio devices (SDR)[1] from which one constantly transmits a signal that is read and analysed by other nodes. Devices were equipped with 900 MHz transceiver boards. With the software radios a higher sampling frequency than in previous studies is possible and we can also sample the actual channel instead of only tracking the RSSI. In these studies we concentrated on features related to the signal amplitude and derivation of the instantaneous amplitude from its mean. Furthermore, we conducted preliminary studies on passive device free situation awareness by utilising ambient signals from a FM radio station not under the control of the recognition system. In these studies, static environmental changes such as opened doors have been detected with an accuracy of about 0.9 [10] and a first study on suitable features to detect human activities could achieve an accuracy of about 0.8 with a two stage recognition approach [11].

1. http://www.ettus.com.

DFAR is still a mostly unexplored research field. Open research questions regard the optimum frequencies and the impact of the frequency on the classification accuracy, the optimum sampling rate of the signal, the detection range and the impact of this distance on the classification accuracy as well as the minimum signal-to-noise ratio (SNR). Furthermore, a set of activities that can be recognised by RF-based classification is yet to be identified as well as a suitable design of the detection system. In particular, the impact of the count and height of transmitting and receiving nodes has not yet been considered comprehensively as well as even the actual necessity of a transmit node as part of the recognition system since potentially the system might utilise ambient radio. Also, it is not clear whether and how activities of multiple persons can be identified simultaneously and if features exist that enable ad-hoc DFAR systems. A more detailed discussion of most of these aspects is given by Scholz et al. in [9].

In the present study, we identify and evaluate features for the classification of activities from RF-signals in two frequency bands (900 and 82.5 MHz) with systems utilising ambient radio as well as a system-generated signal. Four activities, two dynamic and two static, together with the empty environment are considered.

3 Application Scenarios for DFAR

We believe that DFAR research can provide a foundation for the realisation of an IoT and for Ubicomp in general. The RF-Sensor has a high penetration in common equipment and will be available in virtually all IoT devices. To reduce cost and complexity, hardware designers and application developers might then rather investigate and utilise the common RF-transceiver to sense environmental stimuli than integrating additional sensing hardware. Currently, the information provided by the RF-channel is, although available virtually for free, mostly disregarded and discarded unused.

Apart from modulated data, the signal strength, amplitude fluctuation or noise level provide additional information about environmental situations. In the following sections we exemplify two applications for DFAR in emergency situations and elderly monitoring.

3.1 Monitoring in Disaster Stricken Areas

Despite tremendous efforts, careful preparation and training for a ’worst case’, increased security precautions and costly installations of early warning systems, disaster situations either caused by nature or human intervention frequently strike also highly developed countries. Recent cautionary tales are the flooding in Thailand or also the Tohoku earthquake near Sendai, Japan that let to a devastating tsunami and was the cause of the atomic crisis around the Fukushima-Daichi power plant.

In the time since this event, research efforts have been taken in the search of systems that can assist auxiliary forces in areas where most of the infrastructure is destroyed. One important and urgent issue in such situations is the search for survivors and injured persons that might reside, for instance, in partly destroyed buildings [60], [61].

When the existing infrastructure is destroyed, RF-sensing might provide a cheap and wide-ranging alternative to assist rescue forces. With a single RF-transmitter such as an RF-radio tower or a base station, a large area cannot only be supplied with voice and data communication but the fluctuation in RF-channel characteristics might be employed to detect individuals and identify their status from activities such as lying, crawling, standing or walking. Auxiliary forces might bring out a network of RF-transceiver devices in order to monitor an area via RF-channel fluctuation as part of their professional routine while at the same time establishing communication means via this RF-transceiver infrastructure [62]. The range, optimum installation height and features for ad-hoc operation are still open research questions for DFAR but the results presented in this work show that assistance in such scenarios can be provided by RF-sensing (although due to the lack of prior training the set of activities recognised might be reduced, for instance, to 'some movement' and 'some static alteration'). These additional sensing capabilities come virtually for free on top of the installation of wireless communication.

3.2 Supporting Well-Being in Domestic Areas

Most accidents happen at home. The primary reason for these accidents are falls which make up about 40 percent of the total number of accidents [63]. Most of these accidents leave the affected person in an unusual posture such as lying at an unusual location. While the automatic detection of fall and fall prevention has gained large interest in the research community and various approaches have been proposed, these alarm system either need body-attached sensors, require the installation of a complex infrastructure or have strong privacy related implications as, for instance, video based systems [64], [65], [66]. By utilising the RF-sensor for this kind of detection we would reduce privacy issues, avoid the need of having to carry sensors and ideally reduce installation requirements to a minimum.

The sensor could further become a crucial component of (Health) Smart Home systems [67], [68] relieving users from the necessity to wear a device. In fact, for Smart Home systems, the sensor needs to provide a rough localisation capability as well as the recognition of at least a basic set of activities of daily living. Among such activities are walking, standing and sleeping [69].

Considering the demographic change in developing and developed countries, the application of the RF-sensor for alarm systems or Smart Homes could further play an important role towards the extension of self-sustained living of the elderly. The present study illustrates the potential of the ubiquitously available RF-sensor for the detection of relevant activities in Smart Home environments.

4 Features for DFAR

In the following we discuss the RF-based features we considered and their achieved classification accuracy. We identify a set of three most relevant features for active and passive DFAR systems.

For our active DFAR system, we deploy a USRP SDR transmit node constantly broadcasting a signal $m(t)$ at a frequency of $f_c = 900$ MHz. In the passive DFAR system a FM radio signal $m(t)$ from a local radio station at $f_c = 82.5$ MHz is utilised. In both cases, the received signal

$$\zeta_{\text{rec}}(t) = \Re\Big(m(t)e^{j2\pi f_c t}\text{RSS}e^{j(\psi+\phi)}\Big) \tag{1}$$

is read by one USRP SDR node and is analysed for signal distortion and its fluctuation due to channel characteristics. In equation (1) the RSS denotes the Received Signal Strength. The value ϕ accounts for the phase offset in the received signal due to the signal propagation time. This continuous received signal is sampled from the USRP devices $64 \cdot 10^9$ times per second at distinct time intervals $t = 1, 2, \ldots$ in a resolution of 12 bits.

We considered the following features for activity classification. For all features we employed a window $\mathcal{W}$ of $|\mathcal{W}|$ samples to calculate their value. The blocking or damping of signal components by subjects or other entities impacts the amplitude of the received signal. A feature to measure this property is the maximum peak of the signal amplitude. We calculate it by the difference between the maximum and minimum amplitude within one sample window

$$\mathcal{P}_{\text{eak}} = \max_{t\in\mathcal{W}}(\zeta_{\text{rec}}(t)) - \min_{t\in\mathcal{W}}(\zeta_{\text{rec}}(t)). \tag{2}$$

We utilise the mean amplitude μ of the received signal frequently as a reference value to compare the current amplitude of a signal $\zeta_{\text{rec}}(t)$ to the average amplitude in a training situation:

$$\mu = \frac{\sum_{t=1}^{|\mathcal{W}|}\zeta_{\text{rec}}(t)}{|\mathcal{W}|}. \tag{3}$$

The root of the mean square (RMS) deviation of the signal amplitude $|\zeta_{\text{rec}}(t)|$ to the mean μ is also utilised. With lower RMS we expect fewer alterations in an environment.

$$\text{RMS} = \sqrt{\frac{\sum_{t=1}^{|\mathcal{W}|}\left(\zeta_{\text{rec}}(t)-\mu\right)^2}{|\mathcal{W}|}}. \tag{4}$$

Furthermore, we investigate the second and third central moment that express the shape of a cloud of measured points. The second central moment describes the variance σ^2 of a set of points. It can be used to measure how far a set of points deviates from its mean.

$$\sigma^2 = \frac{\sum_{t=1}^{|\mathcal{W}|}\left(\zeta_{\text{rec}}(t)-\mu\right)^2}{|\mathcal{W}|} \tag{5}$$

Additionally, we consider the third central moment.

$$\gamma = \text{E}[\zeta_{\text{rec}}(t)-\mu)^3] \tag{6}$$

In equation (6), $\text{E}[x]$ defines the expectation of a value x.

All above features are taken from the time domain of the received signal. In the frequency domain, we consider the DC component a_0, the spectral energy $\mathcal{E}$ and the entropy H of the signal.

The feature a_0 represents the average of all samples a Fast Fourier Transform (FFT) was applied to. It describes the vertical offset of an observed signal.

TABLE 2
Best Feature Combinations for the Passive DFAR System

(a) Distinction between dynamic and static activities

accuracy	$\mathcal{P}_{\text{eak}}$	μ	a_0	$\mathcal{E}$	H	σ^2	γ	RMS
.866	x		x			x		
.863	x					x	x	
.861	x		x				x	
.861	x		x					
.861	x						x	

(b) Distinction between standing, lying and empty

accuracy	$\mathcal{P}_{\text{eak}}$	μ	a_0	$\mathcal{E}$	H	σ^2	γ	RMS
.902	x		x					
.898	x	x	x					
.898	x		x				x	
.896	x	x						x
.894	x	x					x	

(c) Distinction between walking and crawling

accuracy	$\mathcal{P}_{\text{eak}}$	μ	a_0	$\mathcal{E}$	H	σ^2	γ	RMS
.817			x		x		x	
.706		x	x					x
.701	x		x			x		
.701	x			x	x			
.701	x					x	x	

(d) Distinction between all five activities: standing, walking, crawling, lying and empty

accuracy	$\mathcal{P}_{\text{eak}}$	μ	a_0	$\mathcal{E}$	H	σ^2	γ	RMS
.694	x				x		x	
.686	x		x				x	
.683	x		x					
.679	x	x	x					
.679	x		x					x

We calculate its ith frequency component as

$$\mathrm{FFT}(i) = \sum_{t=1}^{|\mathcal{W}|} \zeta_{\text{rec}}(t) e^{-j\frac{2\pi}{N}it}. \tag{7}$$

In equation (7) we choose the window size $|\mathcal{W}|$ as the quantity of the samples in the FFT.

The DC component is defined by the first Fourier coefficient $\mathrm{FFT}(i)$ and is separately calculated as

$$a_0 = \frac{\int_{-\frac{|\mathcal{W}|}{2}}^{\frac{|\mathcal{W}|}{2}} (\zeta_{\text{rec}}(t))\, dt}{|\mathcal{W}|}. \tag{8}$$

The signal energy $\mathcal{E}$ can be computed as the squared sum of its probability density of spectrum in each frame. The probability of each spectral $\mathrm{FFT}(i)$ band is

$$\mathrm{P}(i) = \frac{\mathrm{FFT}(i)^2}{\sum_{j=1}^{|\mathcal{W}|/2} \mathrm{FFT}(j)^2}. \tag{9}$$

Consequently, we calculate the spectral energy as

$$\mathcal{E} = \sum_{i=1}^{|\mathcal{W}|/2} \mathrm{P}(i)^2. \tag{10}$$

We compute the entropy of a set of points as

$$\mathrm{H} = \sum_{i=1}^{|\mathcal{W}|/2} \mathrm{P}(i) \cdot \ln(\mathrm{P}(i)). \tag{11}$$

For all possible combinations of up to three of these features we exploited their classification accuracy of the five activities considered in Section 5.1 and in Section 5.2. Table 2 details the accuracy for the best five feature combinations[2] of the passive DFAR system with $|\mathcal{W}| = 32$.

The table distinguishes between one-stage and two-stage classification. For the one-stage classification, all five activities are distinguished in one single classification step. For two-stage classification, first the classifier distinguishes between dynamic (walking or crawling) and static (lying, standing or empty) activities. Then, the final classification is done in one of these classes. We observe that in particular $\mathcal{P}_{\text{eak}}$ and a_0 are well suited to achieve a high classification accuracy.

A high $\mathcal{P}_{\text{eak}}$ value indicates a dynamic activity. The feature is therefore well suited to distinguish between dynamic and static activities. Consequently, for the distinction between the two dynamic activities in Table 2c, this feature is less prominent. The DC-component a_0 mostly represents the vertical offset of the signal. In can therefore serve as an indicator to distinguish whether a person is standing or walking, lying or standing or whether the room is empty.

For the active DFAR system, the most significant features are the variance σ^2, the third central moment γ when applied twice and the minimum over a window of maximum values. We achieved good results for a window size of $|\mathcal{W}| = 20$ which translates to $|\mathcal{W}| = 400$ for features applied on preprocessed data. By the adding further combinations of features, the overall classification accuracy can be further improved slightly.

Generally, for the activities considered, the dynamic activities have a greater number of significant features as they also have characteristic alterations over time. Static activities are therefore in principle harder to distinguish from each other and it will likely not be possible to re-use a trained classifier for static activities without re-training in another scenario.

5 RF-BASED DFAR

In order to explore the activity recognition capabilities and limits of the RF-sensor, we conducted case studies for active and passive DFAR implementations. In particular, three subjects have conducted the four activities lying, standing, crawling and walking in a corridor of our institute. Additionally, the empty corridor was considered as a baseline activity. All experiments have been conducted in after-hours to ensure a controlled environment in which all important external parameters are kept stable. In particular, no additional subjects have been present in the corridor or in adjacent rooms that could have interfered with the

2. The complete table with all results is available at http://klab.nii.ac.jp/~sigg/TMC-2012-01-0047_PassiveDFARAcc.pdf.

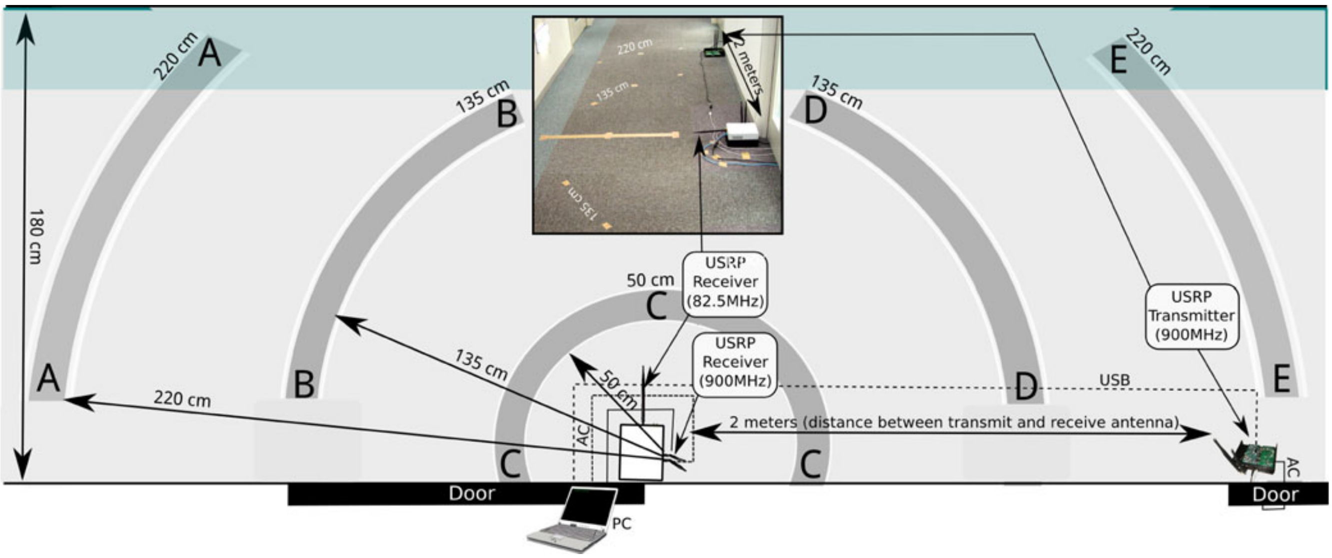

Fig. 1. Schematic illustration of the corridor in which the case-study was performed. Locations at which activities were conducted are marked (A, B, C, D, E). Both receive nodes are located in the center of the recognition area on top of each other.

experimental conditions. Fig. 1 depicts the setting employed for the case study.

The experimental space was divided into five areas with respect to their distance to the receiver. For active and passive systems, the receiver was placed at the same location in the center of the detection area. For the active DFAR system, the transmitter was positioned in two meters distance from the receiver.

The activities were conducted at the five locations which are labelled A, B, C, D, and E. Locations A and E are in a distance of 2.20 meters from the receiver, locations B and D are separated by 1.35 meters and location C is 0.5 meters apart. All locations are arranged in a circle around the receiver in their center.

Each of the three subjects repeated all activities at every location for about 60 seconds. We took arbitrary patterns from these sample sequences for classification.

For the active DFAR system the transmitter constantly modulated a signal to a 900 MHz carrier which was then sampled at the receiver at 70 Hz. USRP 1 devices[3] were utilised as transmitter and receiver with RFX900 daughterboards[4] and VERT900 Antennas[5] with 3dB antenna gain.

The receiver of the passive DFAR system sampled a signal from an ambient FM radio station at 82.5 MHz with a sample rate of 255 kHz. We employed a USRP N200[6] device with a WBX daughterboard[7] together with a VERT900 Antenna[8] with 3dB antenna gain [11].

5.1 Active Device-Free Activity Recognition

For the detection of the described activities with our active DFAR system we utilise a one-stage classification approach. In particular we use as features the mean μ, the variance σ^2, the third central moment γ, the RMS, the count of amplitude peaks within 90 percent of the maximum, the distance of zero crossings, the Energy $\mathcal{E}$ and the entropy H, over a window of 400 samples.

For classification we utilise a k-nearest neighbour (k-NN) classifier with $k = 10$ and a decision tree (DT). Fig. 2 depicts values for the variance σ^2 and the third central moment γ applied twice for part of the sample data. Distinct activities are clearly distinguishable in this plot already.

From this data we observe that activities conducted at locations A and B are seemingly harder to distinguish from the empty case. The reason is that activities at these locations are conducted relative to the transmitter behind the receiver and therefore have less impact on the received signals.

Classification results after 10-fold cross validation are depicted in Table 3. Table fields with very low values (i.e., 0.0) are left blank. The table depicts the classification accuracy when classifiers for the five activities empty, walking, standing, lying, crawling have been trained on features obtained for all five locations and subjects. Due to the challenging feature value fluctuations for locations A and B we

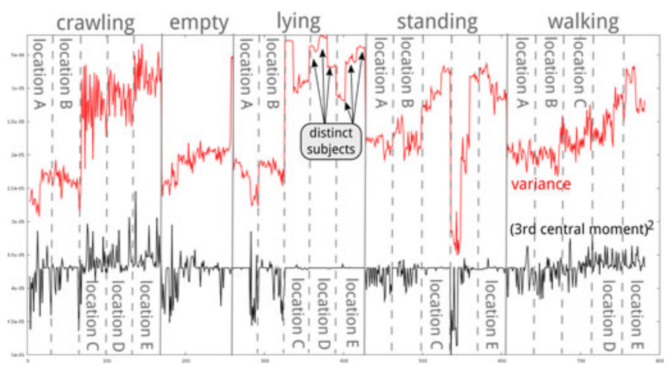

Fig. 2. Exemplary feature samples (variance and twice applied third central moment; over 400 samples each) from all activities, locations and subjects for active DFAR.

3. https://www.ettus.com/product/details/USRP-PKG.
4. https://www.ettus.com/product/details/RFX900.
5. https://www.ettus.com/product/details/VERT900.
6. https://www.ettus.com/product/details/UN200-KIT.
7. https://www.ettus.com/product/details/WBX.
8. https://www.ettus.com/product/details/VERT900.

TABLE 3
Classification of Activities Conducted by Three Subjects at Locations A to E by a k-Nearest Neighbour and a Decision Tree Classifier in an Active DFAR System

(a) Confusion matrix for the k-NN classifier over samples from all locations and subjects

	Classified				
	crawling	empty	lying	standing	walking
crawling	**.713**	.024	.06		.204
empty	.022	**.593**	.187	.121	.077
lying	.042	.048	**.743**	.144	.024
standing	.011	.067	.078	**.777**	.067
walking	.166	.029	.034	.051	**.72**

(b) Confusion matrix for the classification tree classifier over samples from all locations and subjects

	Classified				
	crawling	empty	lying	standing	walking
crawling	**.659**	.006	.054	.024	.257
empty	.055	**.582**	.154	.121	.088
lying	.054	.042	**.784**	.102	.018
standing	.022	.056	.095	**.771**	.056
walking	.189	.023	.011	.057	**.72**

have not been able to achieve a higher accuracy in this case. In particular, we notice that the distinction of the empty class is hard for the classifiers since other activities conducted at locations A and B have a similar feature value footprint. The overall classification accuracies are 0.714 and 0.722 for the classification tree and the k-NN classifier as depicted in Table 4.

The table also shows the Brier score and the Information score as defined by Kononenko and Bratko [70]. These basic accuracies can be improved when classifiers are trained at specific locations and when the classification of activities is segmented for distinct locations as derived in the next sections.

5.1.1 Spatial Impact on Accuracy

To improve accuracy we spatially restricted the classification area. In particular, we utilised feature values only from activities conducted at one distinct location (A,B,C,D or E). Table 5 shows the classification results for location C. The classification accuracy is increased in this case compared to the previous general setting. This is also due to the subjects conducting activities in only about 50 cm distance from the receive antenna. The impact on the signal is therefore significant.

With increasing distance to the receiver, the classification accuracy slowly deteriorates as visible in Table 6. The table depicts the classification accuracy of the k-NN classifier. Classification accuracies for the decision tree are comparable as shown in Table 7. We observe that indeed locations E, D and C achieve best classification results. The impact of reflected signals from an action conducted behind the receiver quickly diminishes, so that the classification accuracy of activities conducted at these locations (A and B) quickly worsens with distance.

5.1.2 Localising an Action

In the previous case, the classifiers were trained for actions of a specific location without considering actions taking place at other locations. We now train the classifiers on all five activities at all five locations, respectively. The action 'empty' is identical regardless of the location. Overall, we then distinguish between 21 classes. Table 8 depicts our results.

We observe that the right action is classified for the right location most often. Moreover, we see a locality in the classifications. Misclassifications are seldom in different activities but most often regarding the correct activity in a neighbouring location. With increasing distance to the place where the action was trained, the misclassification error increases. The distance between locations was 85 cm. We therefore conclude that a localisation of activities is possible alongside classification with an error of less than 1 meter. We further observe that the static activities standing and lying as well as the dynamic activities walking and crawling are harder to distinguish for the classifier since their features are not so well separated.

5.1.3 Summary on Active DFAR Studies

All five activities are classified with varying accuracy depending on the setting considered. Higher accuracy can be achieved when the activities are conducted near the receiver node or between the transmitter and receiver. With increasing distance to the receiver the classification accuracy deteriorates. When the activities are trained at various locations, a localisation of the classified activity within less than 1 meter radius is possible.

5.2 Passive Device-Free Activity Recognition

In the previous section we considered an active transmitter as one part of the classification system. The disadvantage in such a system is that in a practical situation, a separate transmitter has to be brought out and positioned in the proximity of the receiver that is constantly transmitting. However, since the freely available frequency spectrum is sparse, we can assume to be exposed to some kind of radio signals continuously. The highest coverage is probably reached by FM radio. We attempt to utilise ambient FM radio signals from a nearby FM radio station in order to detect the five activities described above in the same setting. In our case study, the FM-receiver was placed on top of the 900 MHz USRP receiver to sample ambient signals. Samples have been taken simultaneously to the active DFAR studies described above. We utilise 10 fold cross validation with k-NN and decision tree classifiers. A two-stage classification approach with the feature sets that reached best classification accuracy was shown in Table 2).

Table 9 details the classification accuracy when activities are conducted at location C only and classifiers are trained only on these feature values. The table depicts the median classification accuracy and the variance over 10 separate

TABLE 4
Accuracy, Information Score and Brier Score for the Classification Algorithms

	Accuracy	Information score	Brier score
Classification tree	0.716	1.529	0.567
k-NN classifier	0.722	1.518	0.4

TABLE 5
Classification of Activities Conducted by Three Subjects at Location C by a k-Nearest Neighbour and a Decision Tree Classifier in an Active DFAR System

(a) Confusion matrix for the k-NN classifier over samples from all subjects at location C

	Classified				
	crawling	empty	lying	standing	walking
crawling	**.848**			.03	.121
empty		**.978**			.022
lying			**.839**	.161	
standing			.108	**.892**	
walking	.143				**.857**

(b) Confusion matrix for the classification tree classifier over samples from all subjects at location C

	Classified				
	crawling	empty	lying	standing	walking
crawling	**.727**	.03	.03	.03	.182
empty		**.978**	.022		
lying		.032	**.677**	.29	
standing	.054	.027	.135	**.784**	
walking	.2				**.8**

TABLE 6
Classification of Activities Conducted by Three Subjects at Locations A, B, D or E by a k-Nearest Neighbour Classifier in an Active DFAR System

(a) Confusion matrix for the k-NN classifier over samples from all subjects at location A

	Classified				
	crawling	empty	lying	standing	walking
crawling	**.556**	.167	.194		.083
empty	.044	**.769**	.055	.066	.066
lying	.125	.25	**.625**		
standing		.286		**.686**	.029
walking	.03	.394			**.576**

(b) Confusion matrix for the k-NN classifier over samples from all subjects location B

	Classified				
	crawling	empty	lying	standing	walking
crawling	**.8**	.133			.067
empty		**.78**	.132	.077	.011
lying		.242	**.727**		.03
standing		.278		**.722**	0
walking	.03	.242	.091	.061	**.576**

(c) Confusion matrix for the k-NN classifier over samples from all subjects at location D

	Classified				
	crawling	empty	lying	standing	walking
crawling	**.765**			.029	.206
empty		**.967**	.033		
lying			**.971**	.029	
standing		.194	.056	**.722**	.028
walking	.111				**.889**

(d) Confusion matrix for the k-NN classifier over samples from all subjects location E

	Classified				
	crawling	empty	lying	standing	walking
crawling	**.676**		.029		.294
empty		**.967**	.033		
lying			**.865**	.135	
standing	.029		.114	**.829**	.029
walking	.263				**.737**

classifications. For ease of presentation, table entries with very low values (0.0 (0.0)) are left empty.

With increasing distance to the receiver, the classification accuracy deteriorates. Naturally, since we utilise ambient signals, the direction in which activities are moved away from the receiver is of minor importance (cf. Table 10). These tables show classification results of the k-NN classifier. Classification accuracies of the classification tree have been comparable. However, we observe that especially the detection of static activities, in particular lying and standing suffer from the increased distance to the receiver. We explain this with the missing LoS signal component between transmitter and receiver. Without a dominant signal component which could have high impact on the received signal when, for instance, blocked, all incoming signal components have equal or similar impact on the signal at the receiver.

TABLE 7
Accuracy, Information Score and Brier Score for the Classification Algorithms in an Active DFAR System

	Accuracy	Information score	Brier score
Location A			
Classification tree	0.674	1.284	0.652
k-NN classifier	0.674	1.309	0.449
Location B			
Classification tree	0.825	1.696	0.35
k-NN classifier	0.735	1.385	0.383
Location C			
Classification tree	0.841	1.702	0.317
k-NN classifier	0.907	1.892	0.129
Location D			
Classification tree	0.832	1.709	0.337
k-NN classifier	0.887	1.846	0.168
Location E			
Classification tree	0.779	1.549	0.442
k-NN classifier	0.851	1.767	0.214

For the utilisation of an ambient signal, the distance to a receiver is more critical than in the active DFAR case. In particular, short of the empty corridor, all classification accuracies drop significantly when activities are conducted at locations remote to the location at which the classifier was trained. Table 11 shows this property for a case in which the classifier is trained from feature values of activities conducted at location C but applied to activities conducted at all five locations.

When training the classifier with feature values from activities conducted at various locations the accuracy decreases (cf. Table 12).

Furthermore, a localisation of the conducted activities as it was feasible for the active DFAR case is hardly possible with the passive DFAR system. The classifier can at most give a hint on the possible location as it can be observed from Table 13. The table details the classification accuracy for all 21 classes considering the activities and their respective locations.

5.2.1 Summary on Passive DFAR Studies

Summarising, we conclude that activity classification is also feasible with a passive DFAR system utilising ambient FM radio signals. We achieved best classification accuracies when the activity was conducted within 0.5 to 1 meters from the receiver. At higher distances, however, the classification accuracy quickly deteriorated and is hardly usable. A passive DFAR system must therefore employ a higher count

TABLE 8
Activity Recognition when Training is Accomplished Including Activities at all Locations in an Active DFAR System

	Classified																									
	crawling					empty	lying					standing					walking				
	A	B	C	D	E		A	B	C	D	E	A	B	C	D	E	A	B	C	D	E
crawling at A	**.528**	.028				.111	.167	.028										.111	.028		
crawling at B	.033	**.867**				.067												.033			
crawling at C	.03		**.455**	.152	.091													.03	.061		.182
crawling at D			.176	**.176**	.147				.029										.029	.118	.324
crawling at E			.088	.176	**.529**																.206
empty	.022					**.681**	.011	.088		.011	.022	.044	.077				.044				
lying at A	.094					.188	**.594**	.125													
lying at B	.091					.152	.152	**.545**									.03	.03			
lying at C									**.677**		.032			.097	.065	.129					
lying at D									.059	**.765**	.088					.088					
lying at E										.162	**.595**			.135		.108					
standing at A						.2						**.686**	.057				.057				
standing at B						.194						.306	**.444**				.056				
standing at C									.054	.027	.054			**.676**		.189					
standing at D		.028				.028			.111			.056		.028	**.472**	.111	.028	.111	.028		
standing at E					.029				.057	.086	.114			.114	.057	**.514**				.029	
walking at A						.152		.061				.061	.061				**.364**	.242	.061		
walking at B	.061	.03				.03	.03	.03				.03			.061		.303	**.364**	.061		
walking at C			.086												.029		.029	.086	**.657**	.114	
walking at D			.056	.028															.139	**.75**	.028
walking at E			.158	.184	.158				.026							.026			.026		**.421**

TABLE 9
Classification of Activities of all Subjects Conducted at Location C by a k-NN and a Classification Tree Classifier in a Passive DFAR System

(a) Confusion matrix for the k-NN classifier

	Classified				
	empty	lying	standing	walking	crawling
empty	**.942** (.152)		.058 (.008)		(.001)
lying		**.773** (.268)	.027 (.007)	.093 (.021)	
standing	.093 (.024)	.027 (.005)	**.853** (.236)	.027 (.005)	
walking	.0 (.001)	.026 (.008)	.077 (.014)	**.795** (.261)	.103 (.032)
crawling	.0 (.001)	.121 (.038)	.014 (.004)	.176 (.071)	**.689** (.214)

(b) Confusion matrix for the classification tree classifier

	Classified				
	empty	lying	standing	walking	crawling
empty	**.986** (.008)		.014 (.003)		
lying		**.787** (.252)	.013 (.004)	.133 (.006)	.067
standing	.027 (.006)	.013 (.004)	**.933** (.009)		.027 (.005)
walking		.026 (.005)	.077 (.014)	**.769** (.210)	.128 (.033)
crawling		.108 (.031)	.027 (.006)	.135 (.045)	**.730** (.245)

TABLE 10
Classification of Activities of all Subjects at Locations A,B,D and E by a k-NN Classifier

(a) Confusion matrix for the classification at location A

	Classified				
	empty	lying	standing	walking	crawling
empty	**.812** (.231)	.145 (.074)		.014 (.006)	.029 (.010)
lying	.155 (.091)	**.239** (.177)	.155 (.066)	.169 (.073)	.282 (.139)
standing		.27 (.098)	**.893** (.158)		.080 (.004)
walking	.054 (.003)	.162 (.055)		**.649** (.294)	.135 (.042)
crawling	.053 (.009)	.027 (.004)	.093 (.007)	.120 (.007)	**.707** (.302)

(b) Confusion matrix for the classification at location B

	Classified				
	empty	lying	standing	walking	crawling
empty	**.783** (.243)	.072 (.009)	.116 (.009)	.0 (.002)	.029 (.006)
lying	.0 (.001)	**.507** (.419)	.440 (.338)	.053 (.006)	
standing		.214 (.110)	**.786** (.208)		
walking	.035 (.005)	.047 (.006)	.012 (.003)	**.659** (.361)	.247 (.157)
crawling	.013 (.003)	.041 (.009)		.230 (.108)	**.716** (.293)

(c) Confusion matrix for the classification at location D

	Classified				
	empty	lying	standing	walking	crawling
empty	**.875** (.186)		.125 (.045)		
lying		**.758** (.308)	.242 (.112)		
standing	.222 (.097)	.25 (.113)	**.500** (.301)		.027 (.012)
walking	.0 (.001)	.120 (.034)	.173 (.044)	**.680** (.143)	.027 (.005)
crawling		.214 (.085)	.071 (.026)	.262 (.063)	**.452** (.296)

(d) Confusion matrix for the classification at location E

	Classified				
	empty	lying	standing	walking	crawling
empty	**.725** (.262)	.087 (.021)	.159 (.034)	.029 (.004)	
lying	.289 (.103)	**.461** (.186)	.145 (.032)	.105 (.028)	.0 (.001)
standing	.130 (.041)	.273 (.125)	**.558** (.371)	.039 (.004)	
walking	.025 (.007)	.120 (.058)	.025 (.004)	**.667** (.286)	.160 (.071)
crawling	.026 (.007)	.013 (.004)		.171 (.068)	**.789** (.228)

of receive devices but can omit a dedicated transmitter. In short distance, classification accuracy is comparable to active DFAR systems.

6 CONCLUSION

We have proposed a classification scheme for device-free radio-based activity recognition systems. Following this scheme, we considered non-ad-hoc, active and passive, device-free activity recognition systems.

Classification was achieved by k-NN and decision tree classifiers with similar classification accuracy. For one-stage and two-stage active and passive DFAR systems we derived a set of most significant features with respect to their classification accuracy in our case studies. The presented work is the first to detect the considered activities from RF-channel measurements and also the first to do this with active and passive DFAR systems. Despite some recent advances on device-free radio-based localisation systems, this is also the ;first study to combine an activity recognition and

TABLE 11
Accuracy for the k-NN Classifier When Training is Accomplished with Activities from All Subjects Conducted at Location C only in a Passive DFAR System

	Classified				
	empty	lying	standing	walking	crawling
empty at A	**1.0**				
lying at A	.355	**.156**	.298	.085	.106
standing at A		.691	**.215**	.054	.04
walking at A	.068	.102	.245	**.251**	.333
crawling at A	.094	.168	.309	.342	**.087**
empty at B	**1.0**				
lying at B	.207		.427	.327	.04
standing at B	.446		**.331**	.223	
walking at B	.053	.059	.112	**.647**	.129
crawling at B	.034	.047	135	.608	**.176**
empty at C	**.986**		.014		
lying at C		**.787**	.013	.133	.067
standing at C	.027	.013	**.933**		.027
walking at C		.026	.077	**.769**	.128
crawling at C		.108	.027	.135	**.730**
empty at D	**1.0**				
lying at D	.113	**.035**	.423	.373	.056
standing at D	.165	.152	**.468**	.171	.044
walking at D	.04	.228	.201	**.262**	.268
crawling at D	.054	.118	.344	.269	**.215**
empty at E	**1.0**				
lying at E	.408		.355	.224	.013
standing at E	.442	.013	**.325**	.201	.019
walking at E	.204	.043	.228	**.42**	.105
crawling at E	.099	.132	.152	.503	**.113**

localisation in one classification algorithm on a common set of features. For the activities lying, crawling, standing and walking we were able to localise them within less than 1 meter in USRP-SDR-based case-studies with the active DFAR system.

The results of this study effectively enable the use of arbitrary wireless devices as sensing equipment.

Still, open challenges remain and present future research questions for radio-based activity recognition systems. Among them are the development of algorithms and features which reduce the amount of training effort or the amount of additional required knowledge in order to use the RF-sensor in a different setting. We further need to investigate the required coverage, height and relative location of the sensor in order to deduce how the number of sensor entities affect the resolution of the system. Other questions include the activity detection of multiple persons or the inclusion of mobile nodes within a DFAR system.

Nevertheless, with the presented investigation results it could be shown that the RF-sensor can support applications such as monitoring of emergency situations or the creation of Smart Home systems. In both applications the sensor could not only provide a classification accuracy comparable to the currently used technologies but also provide novel services, such as detecting non-cooperating persons, and increases the level of convenience, for instance, by not having to wear an actual monitoring device. Based on these findings and the truly pervasive character of the underlying physical entity we believe that RF-based sensing can be essential in the pervasive systems of the upcoming Internet of Things.

TABLE 12
Classification of Activities at all Locations by a k-NN and a Classification Tree Classifier Trained on Activities Conducted by All Subjects on Location C Only in a Passive DFAR System

(a) Confusion matrix for the k-NN classifier

	Classified				
	empty	lying	standing	walking	crawling
empty	**.949**		.043	.007	
lying	.154	**.473**	.241	.065	.067
standing	.192	.156	**.577**	.049	.025
walking	.054	.128	.126	**.476**	.216
crawling	.032	.153	.126	.199	**.490**

(b) Confusion matrix for the classification tree

	Classified				
	empty	lying	standing	walking	crawling
empty	**.978**		.022		
lying		**.500**	.198	.301	.001
standing			**.787**	.212	.001
walking		.001		**.824**	.130
crawling			.051	.433	**.516**

TABLE 13
Passive DFAR Classification Accuracy of the k-NN Classifier and Localisation of Activities When Training is Accomplished Including Activities At All Locations

	Classified																				
	crawling					empty	lying					standing					walking				
	A	B	C	D	E		A	B	C	D	E	A	B	C	D	E	A	B	C	D	E
crawling at A	.134	.027	.027	.067	.013	.014	.027	.04	.027	.027	.02	.06	.047	.013	.067	.04	.08	.034	.06	.081	.094
crawling at B	.007	.304	.041	.014	.155	.014	.027	.007		.02				.027	.007	.007	.007	.135	.101	.054	.074
crawling at C	.02	.048	.476	.02	.014		.007	.027	.109					.007	.007		.041	.061	.068	.082	.014
crawling at D	.086	.022	.043	.097	.054	.011	.022	.075		.065	.011	.108	.022	.022	.043	.043	.032	.065	.075	.065	.043
crawling at E	.007	.106	.013	.046	.285	.02		.007	.04	.106					.007			.172	.079	.02	.093
empty						1.0															
lying at A	.035	.014	.007	.021	.007	.141	.206	.092	.014	.043	.043	.014	.028	.071	.035	.05	.071	.021	.014	.050	.021
lying at B	.08	.013	.02	.047	.007	.027	.1	.147		.033	.087		.073	.047	.06	.133	.007		.02	.027	.073
lying at C	.04		.107		.047		.013		.638			.054		.007	.02		.013	.013	.007	.04	
lying at D	.014	.035	.007	.056	.134	.007	.014	.035		.282	.035	.028	.028	.042	.049	.028	.035	.014	.063	.063	.028
lying at E	.026			.007		.125	.013	.072		.033	.191		.118	.086	.066	.145	.02		.02	.013	.066
standing at A	.06			.067			.013		.054	.013		.544		.007	.121	.013	.04			.067	
standing at B	.036			.014		.115	.014	.101		.036	.144		.223	.029	.072	.173	.007		.007		.029
standing at C	.007	.027	.007	.013		0.18	.08	.053	.033	.027	.093	.007	.033	.293	.067	.007	.04	.007	.007	.007	.013
standing at D	.063	.006		.025	.013	.013	.044	.063	.013	.025	.063	.114	.063	.07	.228	.07	.013		.025	.082	.006
standing at E	.039			.032	.006	.102	.071	.123		.013	.117		.156	.026	.065	.13	.013	.013	.013	.026	.052
walking at A	.061	.007	.048	.027	.007	.021	.048	.007	.027	.034	.034	.034	.014	.054	.02	.02	.395	.027	.007	.088	.02
walking at B	.006	.153	.071	.018	.147	.006	.029	.012	.012	.029				.012		.012	.024	.224	.147	.024	.076
walking at C	.032	.097	.045	.039	.084		.013	.013	.013	.045	.013			.006	.006	.013	.006	.155	.258	.058	.103
walking at D	.06	.04	.067	.04	.027		.074	.04	.04	.054	.007	.087		.027	.067	.02	.067	.020	.054	.154	.054
walking at E	.093	.074	.012	.024	.148	.037	.006	.056		.031	.062		.031	.024	.006	.043	.019	.056	.08	.062	.136

ACKNOWLEDGMENTS

The authors are grateful to Mario Hock, Nadezda Sackmann and Antonius Karatzoglou for performing parts of the activity recording trials. They would further like to acknowledge partial funding by a fellowship within the Postdoc-Programme of the German Academic Exchange Service (DAAD) and partial funding by the German Federal Ministry of Education and Research (BMBF) through the Koordinator project.

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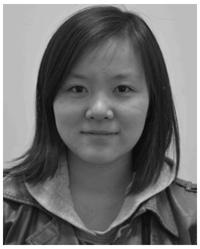

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