Challenges for device-free radio-based activity recognition

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Abstract. In this paper we provide an introduction to the relatively new field of device-free radio-based activity recognition (DFAR). While the research in device-free radio-based localization (DFL) has progressed in recent years, only few works exist which distinguish activities using this approach. Thus, we give an overview over the most important works investigating device-free localization and activity recognition. We then discuss how radio-based activity recognition may profit from the current state of research and which challenges need to be addressed to enable the radio based recognition of activities. Finally, we present our vision of future DFAR systems and our plans for future work.

Key words: device-free radio-based, localization, activity recognition

1 Introduction

Activity recognition is a research field in pervasive computing in which systems are designed and investigated which interpret sensor data to conclude the current and possibly future activities of a user. Thereby usually sensors are attached to a users' body, integrated into an object with which he may interact or installed in his environment. However, these most commonly used approaches have their drawbacks as the wearable device needs to be put on or installed, devices needs to be modified or the infrastructure based system needs to be installed. We believe that the utilization of radio signal analysis for device-free activity recognition may provide an interesting sensor option which could work around some of the existing systems' issues and limitations.

Most prominently and intuitively radio signals are used for wireless information transfer. Common application examples include Wifi, cellular networks and, of course, wireless sensor networks (WSNs). In these applications effects which influence the emitted signals are usually disruptive and unwanted. However, there also exist technologies such as RADAR, GPS or radio telescopes which leverage some of these effects.

While these technologies may also provide interesting approaches to radio-based activity recognition we will focus on the utilization of typical sensor node frequency bands and transmission schemes in this paper. Thence, we will not consider purely reflection based measurement systems (RADAR) or wideband systems (like UWB). Also these may have a priori restrictions related to their technology. For instance, in the case of UWB a line of sight (LOS) path between nodes is mandatory (or the knowledge of the time of flight of the LOS). While a large community exists around traditional WSN location research it is important to note that in this paper we focus on radio signal analysis in order to derive information about an object which is not part of the wireless network i.e. an object which is device-free.

The paper is structured as follows: section 2 gives a brief introduction to radio wave effects and the first work from the WSN community investigating the effects which spawned the device-free radio-based localization (DFL) research. More recent research from this field is then presented in section 3, while the few works on device-free activity recognition are presented in section 4. The publications and implications of section 3 and 4 are discussed in section 5. Section 6 concludes the paper with a list of challenges and next steps.

2 Radio-based sensing in WSNs: general effects and initial experiments

Radio waves are electromagnetic waves with a frequency ranging from 3kHz to 300GHz. Electromagnetic waves are affected by various effects when propagating through space. The magnitude of these effects primarily is a function of signal frequency, transmission medium and objects encountered during propagation. Such effects include reflection (when the wave partially bounces off an object), refraction (change of direction when passing from one medium to another), absorption (loss of energy when an object is hit), diffraction (when waves are bend and spread around an obstacle), scattering (wave bounces off in multiple directions) and polarization (orientation of the oscillations of the waves can change upon interaction).[8] Further on, in free space electromagnetic waves follow the inverse-square law i.e. the power density of the signal is in inverse ratio to the square of the distance from the transmitter.[8]

Another aspect of radio wave propagation is multipath propagation. Typically, the transmitters' antenna will emit radio waves in various directions (e.g. omnidirectional antenna) or angles (e.g. directional antenna). Also some of the above enlisted effects occur at the same time. For instance, a radio wave may propagate through an object but part of it will be reflected on its surface and some of its energy is absorbed by the object. After this interaction there are now (at least) two radio signals propagating in different directions but originating from the same source. Radio signals originating from the same source, which reach the receiver by two or more paths, are called multipath signals or components. The power of the received signal is typically a sum of some of these destructive or constructive multipath components.

In WSNs, there is usually a single parameter available which gives an indication of the received signals' power. This parameter is the received signal strength indicator (RSSI) which is typically a scalar value. This parameter may be understood as a complex function of the above described effects over the course of the signals through space until entering the receivers' antenna.

In 2006, Woyach et al. [15] conducted RSSI-based experiments and found that the localization of objects in-between nodes without wireless connectivity could be feasible. They observed a difference in RSSI changes by an object moving between (resulting in shadowing of signal paths) and in the vicinity (causing small-scale fading) of two transceivers and identified the RSSI variance as a feature allowing insights into the type of movement. Also fluctuations in variance were different depending on the trajectory of an object, network topology and geometry of the environment.

They also showed that the movement of a node in the network has a stronger impact on RSSI than the movement of an object external to the network as in the latter case typically a smaller number of signal paths is affected. The same experiments were also used to undermine a radio wave property Woyach et al. referred to as spatial memory. Therein they showed that after any kind of temporary change in the environment the RSSI returned to the same measurement values seen prior to the change. Fig. 1 gives a simplified illustration of these experiments.

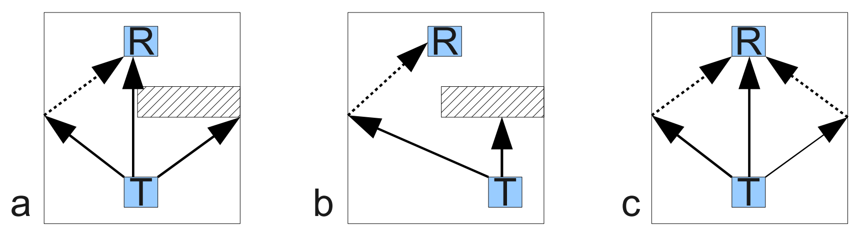

Fig. 1. Experiments conducted by Woyach et al. regarding WSN node movement and changes in the environment. In a) a receiver R and transmitter T are located inside a room. An object in the room is partially shadowing signals from T. In b) the transmitter is moved behind the object so that R will now only receive reflected signals. While the shadowing will affect RSSI, the movement of T to this new position will also create strong RSSI fluctuations. In c) the object is removed adding additional reflected and LOS paths between T and R. Reverting from situation c) to a) will give similar RSSI values as before.

In the same paper also accelerometer and RSSI measurements were compared and they showed that in some cases the radio sensor seemed to be more sensitive than the accelerometer.

They also conducted an experiment directed at link asymmetry i.e. the difference in signal strength when exchanging the roles of transmitter and receiver. While a common reason for link asymmetry is caused by the different orientation of antennae[3], the introduction of a volatile obstruction (new/moved object) may also strongly alter symmetry properties of radio links. Using 2.4 GHz WSN nodes and an obstructing of the LOS using a metal object at various locations

Woyach et al. showed that the measured asymmetry can be up to the order of one magnitude.

In another experiment a total of four 2.4 GHz WSN nodes were placed in the corners and in the middle along the walls of a 5x7m room. Compared to measurement in the static room RSSI differences were observed when a chair was placed in the room or two people moved around.

Finally, they compared how RSSI is affected when a human moves in the LOS with respect to two types of carrier frequencies. In expectation to general physics theory (inverse relation of frequency and attenuation) they reported that the fluctuation of 2.4 GHz signals was about the double compared to 433MHz. The fluctuations disappeared when the movement stopped.

These initial experiments by Woyach et al. spawned a number of related publications which we will review in the next two sections.

3 DFL: Device-free radio-based localization

In this section we will review publications which build on the results of Woyach's experiments (cf. section 2) in order to investigate device-free passive localization (DFL) systems[16]. These systems as defined by Youssef 2007[16] are systems which localize or track a person using analysis of radio signals while the person itself is not required to carry a wireless device.

This research is highly relevant to this paper as algorithms, models and node setups from this domain are investigated regarding the impact of human movement on RSSI. The reviewed publications are ordered by their research focus. An older but more detailed overview of DFL research can be found in [6].

3.1 Spatial coverage and adaptive machine learning

Zhang et al.[18] used a test bed with 870MHz WSN nodes arranged in a grid and attached to the ceiling in 2.4m to investigate the influence of movement on radio links. They showed that for each link on the ceiling an elliptical area on the floor exists for which RSSI fluctuation caused by an object moving this area exceeds measurements in a static environment.

They also investigated the relation of received signal power, node distance and transmit power. They reported that for distances of 2m and 3m they can regulate the impact of an object on RSSI by adjusting the transmission power. Setting transmission power too low will lead to weak effects on RSSI when introducing an object. For longer distances regulation of the transmission power has no influence as the transmission power cannot be increased enough to allow a sufficient impact of objects on the signal (i.e. they cannot be separated from the noise in the static measurement). 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 2m to 5m for the tested WSN nodes. From this experiment they concluded that adjusting the power in respect to the localization algorithm and topology can improve accuracy.

Recently[17], they also investigated methods to reduce latency of their DFL system and to gain a better understanding of topology requirements. In this work they divided the monitored room into hexagonal areas. Adjacent areas used different communication channels. Each of the hexagons was built of six triangles which followed a predefined TDMA slotting scheme. Tracking was realized using support vector regression (SVR). This machine learning based classifier would usually require the typical training-testing iterations when new monitored areas are added. However, Zhang et al. developed an adaptive learning approach using which new triangles can be added to the system based on only three sample points. Using SVR and this special topology an object position could be derived with an accuracy of around 1m and an update frequency of 3.8Hz (previously 0.5Hz).

3.2 Accurate presence detection and fingerprinting

In their early experiments Youssef et al.[16] concentrated on the detection of people. For their experiments they set up classical 802.11b wifi nodes in the corners of a room. Two of these nodes sent packets at 100ms, while the two other nodes recorded the RSSI of the received packets. For detection the features 1) moving average RSSI and 2) moving average RSSI variance were compared. For both approaches two types of moving averages were calculated: a longer window (long-term behavior) which was used to compare against a shorter window (short-term behavior) in order to detect a change. Among the different window lengths they tested they achieved a 100% accuracy with both approaches. In this work they also presented a first localization system based on fingerprinting. Therewith they achieved an accuracy of 90% accuracy for the given setup.

In a later publication[12] they presented the more advanced Nuzzer DFL system which was evaluated in a large-scale typical office environment. Using only 3 access point and 2 monitoring points with a data collection at 5Hz they achieved a 1.82 median distance error. As before a passive radio map was constructed during offline phase, then a Bayesian-based inference algorithm estimated the most probable user location.

Recently[4] they presented a new system for the accurate detection of human motion in a monitored area. Therein they used methods from anomaly detection and achieve 6% miss detection and a 9% false alarm rate when evaluating the system in two real environments. Especially interesting in this paper is the comparison of features (mean of RSSI vs. standard deviation of RSSI) in respect to sensitivity to human movement and stability. They reported that standard deviation turned out to be more stable to changes in the environment but more sensitive to human movement when comparing new recordings with data from two weeks before. The system also advanced their previous work as only a calibration phase of around 2 minutes in a static environment was needed. They further implemented techniques to counteract effects of environmental dispersion. This was accomplished by continuously adding newly measured data which did not trigger the detection.

3.3 Radio tomographic imaging and statistical modeling

Wilson and Patwari approached DFL by creating visualizations of measurements from WSN node arrays. As source for their radio tomographic imaging (RTI) they use the two-way (cf. link asymmetry in section 2) RSSI variance[13] or RSSI mean fluctuations[14] between nodes arranged in a rectangle surrounding the monitored area. Using the latter system they also showed the robust localization of two people simultaneously. In all of their experiments WSN nodes are deployed on stands in approx. the height of a human torso (in order to maximize human motion effect on RSSI).

They further introduced a statistical model[5] to approximate the position of a person based on RSSI variance. This model combines two previously known radio channel models and makes the following simplifications: 1) both transceivers have an omnidirectional antenna, 2) modeled effects include scattering and reflection only, 3) all scattering objects (all static obstructions which either cause scattering or reflection) are located in a single plane parallel to the ground and, 4) only a single interaction of each multipath component is modeled.

In this model the motion of an object in the monitored area causes a certain quantity of multipath power to be affected. This quantity can be supplied to the model as the measured variance on a link is approximately linearly related to the total affected power[5].

The model was empirically verified[13] and can be used to explain most of the measurement results reported by other researchers (e.g.[18]). Also in conformance with the findings of others[4], they reported that the variance of the RSSI can be used as an indicator of motion regardless of the average path loss that occurs due to dense walls and stationary objects within the network. In many cases multipath fading even caused the mean signal strength to increase when a human/object obstructed a link. For the evaluation of the model they reported an approximate error of 3ft for a moving individual and of 1.5ft for a stationary moving individual.

Besides those impressive results, no information was given on how the necessary distribution and number of used WSN nodes was found. Also update rates were relatively slow due to the necessity to gather the two-way link information between all nodes. Thus, the number of transmitted packets grew with $O(N^2)$ when N is the number of nodes. Additional processing delays were introduced due to the employment of a Kalman filter used for tracking.

4 DFAR: Device-free radio-based activity recognition

In this section we will give an overview over publications from device-free radio-based activity recognition (DFAR) research. In correspondance to the definition of DFL[16] we define such systems:

DFAR *Device-free Radio-based Activity Recognition system:* a system which recognizes the activity of a person using analysis of radio signals while the person itself is not required to carry a wireless device.

The reviewed DFAR publications are categorized by the used algorithms/approaches.

4.1 DFAR based on adaptive thresholds

In a recent publication of our group[11] we presented a system which detected the situations walking, talking on the mobile phone and the state of the door in a typical office room for a single person. The setup consisted of two software defined radio nodes (SDRs) placed to the right and left side of the door of a typical office room. One node was configured to send a continuous sine signal on the 900MHz band while the other node received and analyzed the signal.

For the detection of walking the number of peak-to-peak amplitudes greater than a trained threshold in a time frame of 50ms was defined as feature. The algorithm checked if the number of such amplitudes was greater than a second threshold which was also determined during training. For the door contexts a static change of amplitude was defined as feature. The threshold for the amplitude detection was also set in a calibration phase prior to the classification. In order to detect a phone call a predefined area of the frequency spectrum was searched for a very strong signal. The searched band was changed every 25ms and the threshold for the signal was hard coded. The scanning of the frequency band was needed to accommodate for the frequency hopping of mobile phones.

The accuracy of these three algorithms was evaluated by presenting all different situations and situation combinations 10 times to the system. The accuracy of the algorithm was on average above 80% for walking in the room, while the other two contexts could be detected with accuracy above 90%. False positives were mostly encountered when the individual passed through the door (false detection of the door context) or the individual moved very slowly or further away from the SDRs so that no activity was detected. The system is depicted in fig.2.

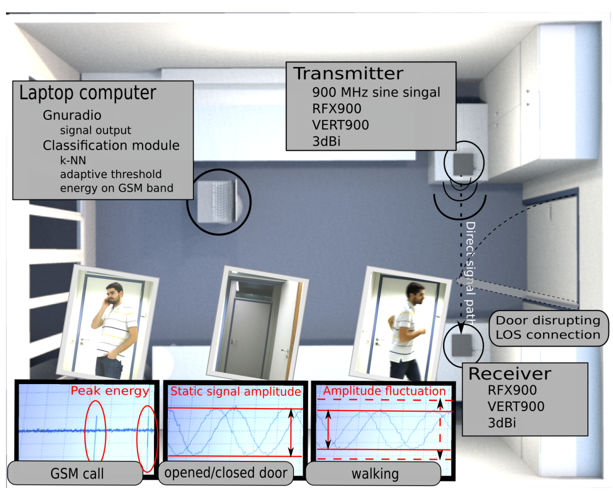

Fig. 2. Schematic illustration of the DFAR system described in section 4.1.

4.2 DFAR based on machine learning

In other publications of our group[10, 9] the results of an extended measurement campaign using machine learning based classifiers were reported. Therein two or three SDRs were installed in a medium sized room. One SDR was used as transmitter of a sine signal which was received by the other SDRs. Tested carrier frequencies were 900MHz and 2.4GHz. Features were root mean square power, signal to noise ratio and average magnitude squared. Features were calculated at 16kHz. Tested ML algorithms were Bayes, k-NN, C4.5 and the rule and tree learners build into the Orange data mining tool[1]. Training and evaluation was performed offline. Examined situations and results were as follows:

Presence/Room state For this trial the defined situations were door open/closed, empty and presence of a single person. The best achieved accuracy was 93% (2.4 GHz, three SDRs, C4.5). For 900MHz accuracy was 83% using k-NN. With only two SDRs the accuracy dropped to 76% (2.4 GHz, k-NN) and 56% (900 MHz, Bayes).

Activity of a person For this trial the following activities performed by a single person were defined as classes: sit, walk and stand. Additionally the empty room was defined. The best results were 64% (2.4 GHz, three SDRs, C4.5) compared to 62% (900 MHz, three USRPs, C4.5). When reducing the number of SDRs accuracies dropped to 17% (2.4 GHz, Tree/Rule Learner) and 61% (900MHz, C4.5).

4.3 DFAR based on statistical modeling

In a recent technical report Patwari et al.[7] also investigated human activities. They presented a system to monitor breathing based on RSS analysis. As in their localization experiments the area to be monitored (i.e. the hospital bed) was surrounded with a number (20) of 2.4GHz WSN nodes and the two-way RSSI was measured with a frequency of 4.16Hz which is sufficient as the maximum breathing rate is 0.667Hz. Using a maximum likelihood estimator they estimated the breathing rate within 0.1 to 0.4 beats accuracy in a 30s measurement window. They further showed that using directional antennas the detection could be improved. The detection was performed by measuring the change of the body in the coverage area of the nodes which affected the WSN links. They also showed that a single link would not have allowed the estimation of breathing frequency and investigated estimation results in dependence of node number.

5 Discussion

In this section we discuss the presented publications on DFL and DFAR and try to deduce next steps and formulate open questions towards DFAR. We start with a guideline for the introduction of novel sensors for activity recognition.

[1] http://orange.biolab.si/

5.1 Introducing the radio sensor for activity recognition

Gordon et al. [2], provided a guideline for the introduction of novel sensors in the field of activity recognition in order to ensure the usefulness of the sensor for consecutive research.

They suggested two kinds of analysis to be conducted: 1) a study regarding the contexts to be identified in order to find out how exactly they affect the physical environment and 2) a study of the novel sensor in order to create a physical/mathematical model of how the sensor creates a representation of its environment and which parameters can be relayed. Based on these studies a mapping could be created to describe which environmental parameters affected by the context are represented in the information relayed by the sensor and which information are lost.

As activity recognition is not a new field, there exist various activities which are well studied and investigated (c.f.[1]). For these activities there are sensors, sensor parameters (configuration, features) and algorithms known to provide good detection results. Hence, Gordon et al. pointed out that in order to evaluate new sensors using three or better known classification methods for specific activities from standard ML frameworks may provide insights into the sensors' potential. They further highlighted that the use of multiple subjects for data gathering as well as the use of different instances of the same sensors are important steps towards a better understanding of the sensors' capability to detect specific activities. For DFAR, especially the last point seems overly important. As a DFAR system has a great number of parameters such as number of nodes, topology, geometry of the environment, carrier frequency etc. While some of these parameters for instance delay, accuracy and sensitivity also need to be considered when looking at classical sensors such as accelerometers; the large number of configurations advises the thorough study and the creation of a model for the radio sensor.

This model could not only provide insights into which activities can be classified successfully but also for which activities the sensor will likely not deliver sufficient information.

5.2 Current status quo of DFAR systems

With the presented publications we have tried to approximate which kind of information the radio sensor can deliver for activity recognition. The DFL community has created models which map motion induced RSSI changes to a location and we found evidence that even stationary motion can be detected robustly using this sensor.

For the presented DFAR publications we found that activity recognition directly on the PHY layer (using software defined radios) but also using classical WSN nodes is feasible with various types of algorithms and for surprisingly small physical activities.

In fact, in part of the reviewed literature[10, 9] we find some of the recommendations of the guidelines fulfilled as various machine learning algorithms which are known to work well, in this case for physical activity recognition, have been applied to typical well known activities (standing, walking, sitting). For the presented literature we summarize the findings as follows:

– RSSI variance and mean have a strong relation to physical motion
– Using these features motion can be detected, localized and tracked
– Variance is more reliable for motion detection
– 433MHz, 870MHz, 900Mhz and 2.4GHz carrier frequencies can be used for motion detection
– 900MHz, 2.4GHz were successfully used for activity and situation recognition
– Adapting carrier frequency or transmission power may improve coverage area/resolution
– Larger number of nodes increases stability/accuracy of classification
– Directional antennae can improve detection
– Determination of noise and static effects is typically needed (calibration)

5.3 Open challenges and future work

Looking at the findings summarized in the previous section we must remark that the current DFAR approaches still seem unstructured and only offer findings based on sample tests. While interesting insights about the feasibility and potential of the radio sensor have been gained, to date it seems that there exists no general solution or methodological approach to DFAR. Thus, currently we are not able to satisfy the requirements discussed in section 5.1.

Even for the small set of successfully recognized activities generalization is restricted. Reasons are the large number of radio sensor configurations which extend beyond the capability description of the employed devices. While the placement of the nodes may be seen in analogy to the placement position of accelerometers or the sensors of a video based systems, additional parameters with strong influence on sensor readings such as room geometry and obstructions cannot be intuitively grasped or described. While there may be analogies also for the number of sensors employed, it is especially the multiplicity and topology of the radio sensor which will be the key to its capability.

Therefore we believe a methodology must be developed for the stepwise creation of DFAR models. In this sense, the statistical approaches of Wilson and Patwari seem to offer good starting points. We further believe that the use of specially adapted simulation tools is mandatory in order to evaluate and proof the developed models. Such tools could further allow extending the evaluation to arbitrary room geometries, obstruction positions and human activities. Possibly, such a simulator could also be directly coupled to a classification system.

Based on our experience with classical WSN communication and location systems, we further believe that different kinds of DFAR systems will exist and they will need different types of models and algorithms. Among them seem to be infrastructure based systems which incorporate knowledge about the environment which goes beyond calibration (for instance, real geometrical information) but also ad-hoc based systems which are calibrate automatically after deployment; the classification performance of these systems will probably differ. An additional type of DFAR could be a system which is completely based on a single passive instance (i.e. a receiver) but which can evaluate signals on multiple carrier frequencies making the whole or a subset of the receivable spectrum part of the sensing process and removing the need for an additional transmitter. Such systems could as well be divided into ad-hoc or infrastructure based types.

Thus, our future work will be directed along the lines of the development of a methodological approach to DFAR, incorporating modeling and simulation as well as real-world measurements. Thereby we plan on utilizing standard and specifically designed WSN nodes but also SDRs - as we believe that the advancement of WSN technology to the level of SDRs will only be a question of technological evolution.

6 Conclusion

In this paper we have reviewed and discussed recent publications from the device-free radio-based localization (DFL) and the device-free radio-based activity recognition (DFAR) field. We have further given a definition for DFAR and presented our vision of future DFAR systems and types.

This paper was motivated by the various articles we reviewed and our own work in the field, from which we found that the use of the radio sensor seems suited especially for the recognition of physical activities. While the presented publications provide a good introduction to these fields, various open challenges remain. To tackle these we have provided a possible approach which is also along the lines of our plans for future work.

We are further excited to see, that even activities with limited physical impact, like breathing can be monitored using a DFAR system and are curious to extend and identify the limits of this technology. Also we must note that while most of the DFAR related publications in this paper aim to recognize some type of physical activity, the potential of the sensor is not limited to this type of activity.

In conclusion, we believe that the emerging field of device-free context recognition (including localization, physical activities, and other activities) will be a major contributor to the realization of the ubicomp vision as radio waves are pervasive, usually considered a calm technology and looking at the used frequency spectrum and distribution the most ubiquitous sensor available.

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