Recent Advances and Challenges in Ubiquitous Sensing

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Abstract—Ubiquitous sensing is tightly coupled with activity recognition. This survey reviews recent advances in Ubiquitous sensing and looks ahead on promising future directions. In particular, Ubiquitous sensing crosses new barriers giving us new ways to interact with the environment or to inspect our psyche. Through sensing paradigms that parasitically utilise stimuli from the noise of environmental, third-party pre-installed systems, sensing leaves the boundaries of the personal domain. Compared to previous environmental sensing approaches, these new systems mitigate high installation and placement cost by providing a robustness towards process noise. On the other hand, sensing focuses inward and attempts to capture mental activities such as cognitive load, fatigue or emotion through advances in, for instance, eye-gaze sensing systems or interpretation of body gesture or pose. This survey summarises these developments and discusses current research questions and promising future directions.

Index Terms—Ubiquitous sensing, Activity recognition, Device-free, sentiment sensing, Pervasive Computing, RF signals,

I. INTRODUCTION

With the stark penetration by smart and mobile devices, we continuously carry sensors of all kinds with us, which monitor every location, situation and activity. More and more applications are exploiting these capabilities. Google Now, fourSquare, Facebook, Twitter and others gather, analyse and exploit large amounts of instantaneous, personalised information. With this data, we can provide novel, intelligent and personalised services to the users.

Development divisions in industry are currently exploring these possibilities, while research is evolving towards new frontiers; we see two main directions of this development:

Parasitic sensing

The parasitic utilisation of environmental, ubiquitously available sources in contrast to sensors on isolated, personal devices.

Sentiment sensing

Interpreting sensor information to recognize mental states, intention, attention emotion and cognitive activities of individuals.

As depicted in figure [1] in traditional Ubiquitous Sensing, the focus of the sensing system lies on the status of a mobile, personal device or sensors attached to an individual and on this individual’s directly observable actions (figure [1a]. The environment (surroundings, crowd, situations) are typically not covered by personal device sensors. Consequently, the device is in a sense short-sighted with its perception limited to an isolated individual. However, considering a complete individual with her plans, emotions, intentions and mental states, classical sensing captures only the surface of that complex human system. Gradually, this focus is shifting towards the recognition of mental states, intention or emotion of individuals while increasingly environmental sensing sources are employed which combine zero installation cost with ubiquitous availability. Only recently, a special issue of the IEEE Pervasive Computing magazine focused on the recognition of attention via sensing modalities [1].

Fig. 1. Classical and future Ubiquitous sensing paradigms

(a) Device- and individual-focused sensing of directly observable states

(b) Parasitic- and Sentiment sensing

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grained information on situations and surrounding entities is available. On the other hand, additional information on mental states can be derived.

Parasitic sensing utilises environmental, ubiquitous sensing sources such as, for instance, audio or radio frequency [2], [3], [4], [5] and thereby extends the perception of the sensing system beyond the boundaries of an individual device or person. Through the utilisation of stimuli from already installed infrastructure, coverage is maximised while installation cost is minimised.

Sentiment sensing focuses on people’s mental state, intention or emotion, for instance, by interpreting eye-gaze information [6], [7], body gesture or pose [8], [9] and thereby directs and extends the perception of a sensing system inwards.

In this survey, we detail current advances towards parasitic and sentiment sensing and discuss open research challenges and promising future directions.

II. OVERVIEW

This section briefly sketches recent development that will foster and induce Parasitic and Sentiment Sensing. Then, in section [III] and section [IV] current advances in these directions are detailed before, in section [V] lively discussed topics and future directions are introduced.

A. The route to Parasitic Sensing

Over the last decade, we have seen remarkable progress in the recognition of human activities or situations [10], [11], [12], [13]. This was driven by several strong developments in related areas. First of all, sensing hardware has been greatly improved (e.g. size, accuracy and also new sensing modalities and sense-able quantities), enabling an enhanced perception of the world through sensors. Also, machine learning has celebrated great successes (algorithms, toolboxes) and has become a mainstream ability that attracts a huge user base towards activity recognition. Furthermore, rapid development in wireless protocols and near-global coverage of some technologies (e.g. UMTS, LTE) enabled the transmission at higher data rates and new usage areas through wireless communication. Last, but not least, novel applications have spread that promote the publishing and sharing of all kinds of data (e.g. Facebook, Line, WhatsApp), which led to novel valuable inputs for activity recognition.

Even given this progress and innovation already, the field is on the verge towards a disruptive next change that will revolutionise usage patterns and open a multitude of new research directions.

Activity recognition in Ubicomp is going towards Big Data with systems developing capabilities to monitor virtually everybody, everywhere and without specifically installing system components at any particular physical location.

Fostered through the advancing Internet of Things and fueled by Opportunistic and Participatory Sensing campaigns (cf. figure [2]), we have been able to follow this development in recent years.

Opportunistic sensing has been viewed as one likely future of sensing [14]. Distributed devices provide their sensing capabilities to neighbouring devices, that are then empowered to access the remotely sensed information or to generate tasks for remote devices to acquire and share this information [15], [16]. This is a promising concept which greatly extends the perception of a mobile device to the joint perception of its neighbouring devices and environment. In the frame of the OPPORTUNITY project [1] an architecture for opportunistic sensing, in particular activity recognition was developed [17], [18]. However, we did not see a broad application and utilisation of Opportunistic sensing yet.

Opportunistic Sensing rises a number of issues not only regarding the mere technical implementation, protocols, mobility and timing. It also touches aspects of privacy and security when alien devices are allowed to access potentially privacy-related personalised information in an uncontrolled manner [16], [19]. In particular, the concept envisions that arbitrary sensors can be accessed so that, apart from the also tremendous challenge to enable the seamless interaction technically, the design of a privacy or security preserving scheme is a nightmare which, with the sheer infinite possibilities and security threats posed by all the sensors, can hardly be solved.

With the proposal of Participatory Sensing [20], the privacy issues of Opportunistic sensing are solved pragmatically. In this sensing principle, remote sensing is restricted to user-controlled mobile devices. Remote devices are still expected to task neighbouring devices for sensed information but human interaction is required in order to approve such request [15]. Consequently, not only is the range of devices restricted to explicitly user-controlled devices with an interactive interface but also the important principle of calmness and unobtrusiveness in Pervasive Computing is disregarded. Instead, the mental load for a user with a Participatory Sensing Device is likely significantly increased as she might be frequently interrupted for interaction.

However, these developments indicate the direction in which activity recognition and sensing as a whole develop. Instead of utilising device-bound sensors with limited range, future sensing will incorporate increasingly environmental sensing sources which have the potential to extend the perception of a

1Opportunity Project website: http://www.opportunity-project.eu/ (Mai 2014)
sensing device beyond its physical boundaries. Consequently, as discussed above, the reliance on explicit hardware sensors in the environment introduces communication overhead as well as technical, privacy and security-related problems. As long as there is no real incentive for device-owners to make sensors on their devices available to the public, they will rather choose to protect their security and privacy as well as their battery by granting exclusively local access to sensors on a device. A less problematic and yet simpler way to extend the perception of a mobile device into the environment is the utilisation of environmental stimuli that can be extracted from the noise of other systems. The parasitic usage of environmental noise has been demonstrated by infrastructure mediated sensing paradigms [21], [22], audio-based [23] and radio-frequency based approaches [24], [2] as detailed in section [11]. We believe that the greatest potential underlies the RF-based systems since (A) RF is available ubiquitously (free frequency spectrum is sparse all over the world), (B) virtually all contemporary electronic devices incorporate an interface to the radio channel and (C) novel technical developments such as OFDM (cf. section [V]) incorporate properties that will likely lead to better recognition accuracies on cheap off-the-shelf consumer devices.

This development is already under way with the community increasingly considering device-free techniques that relieve the monitored individuals from the burden of actually wearing any sensing hardware; and this evolution will continue in the direction of passive, device-free systems which exploit parasitic operation by re-using noisy emissions from ubiquitously available, environmental third-party pre-installed technology.

B. The Route to Sentiment Sensing

Activity Recognition started out with detecting very simple physical states, walking, sitting, standing – modes of locomotion – in the 1990s. We came a long way from these simple classes to tracking a lot of high level activities, like car repair, furniture assembly and Kung Fu exercises [25], [26].

The dedicated sensor systems used in the labs were not easily deployable. Yet, this changed with the advent of the smart phone as general computing platform. Suddenly “cheap” motion sensors were available to everybody. Still using smart phones or other consumer devices brought also new challenges. The position and orientation of the devices was no longer fixed. One had to cope with location and orientation changes of the sensors [27].

Next we saw a push towards physiological sensing, first in the medical application domain then also for more and more sports and fitness research.

Now, more and more people get interested in the brain and brain functions. We gather rich information in cognitive science, psychology medicine and related fields about cognitive processes. Therefore, we have now a sufficient basis to explore cognitive task tracking in everyday life [28].

The first impacts are already visible in the medical domain. Here we see that sensor data from smart phones can predict depression episodes in patients with mental illnesses. Motion data seems to correlate well with some mental states. The same holds for the physiological data. Heart rate, blood oxygen level etc. can tell a lot about our cognitive condition especially combined with motion sensors (e.g. if a user doesn’t move much and his heart rate is increased, it could signify that he’s excited [29]).

Yet, more interestingly, there are a couple of sensor modalities to track brain activity (in-)directly and we see them more and more embedded in consumer devices (e.g. the emotive headset to track brain activity using EEG).

It seems obvious to track brain activity directly using EEG or other brain imaging technologies. However, these technologies have severe limitations; either they are quite expensive and bulky (e.g. magnetic resonance imaging) or they require heavy filtering and analysing. As our skull is quite thick, brain signals are easily overshadowed by motion artifacts etc.

One promising alternative is to use eye tracking, as gaze is directly correlated to some of the higher brain functions. There are two common approaches. Optical eye tracking uses infrared lights and camera to track the pupil. Electrooculography uses electrodes to track eye movements, as our eye is a dipole [30].

III. Device Free/ Radio Sensing

Sensing modalities for activity recognition or monitoring differ in their installation effort and range (cf. figure [3]). The figure summarises popular of these modalities and characterises them for device-bound and device-free (DF) approaches. Within the device-free techniques, we observe a shift of attention towards the evaluation of environmental, measurable quantities of pre-installed third-party systems which are cheap to use and with increasingly wider physical boundaries.

Researchers have shown remarkable accuracy in tracking activities such as, among others, walking, running, cycling, climbing/descending stairs, sleep states and mobile phone usage [84], [85], [86].

However, an implicit requirement of these sensing modalities is that the entity or individual to monitor has to cooperate and actually wear the device (device-bound).

In contrast to this, for device-free approaches, the sensing modality need not be worn by the monitored subject. We can distinguish between classical systems installed particularly for a specific sensing task and systems which are parasitically utilised for sensing but which are originally installed and utilised for other primary purposes. Classical device-free systems cover, for instance, video [55], [56], infrared [58], [57], pressure [62] or ultrasound [63], [64] sensors. A clear disadvantage of these approaches is their high installation effort.

This effort can be mitigated by infrastructure-mediated sensing paradigms [21], [22]. In general, the approach here is to utilise existing installations, for example, in homes or office buildings, for sensing purposes. For instance, pressure patterns in residential water pipes might indicate specific activities/usage of inhabitants [71], [72] or also electromagnetic interference in various electric systems can be utilised to classify activities [69], [70]. However, these sensing capabilities are limited to indoor application and single buildings.
Device-bound

**Inertial sensors**

Accelerometer devices are becoming rapidly ubiquitous in modern day technology [31], [32]. Employed for a broad range of use cases from mere environmental adjustment of devices to the recognition of individual user’s situation [33], [34]. Multiple sensors instrumented at multiple body locations utilised to recognise different activities [35], [36], [37]. Other related sensors are vibration sensors [38], [39], or magnetic resonant coupling [40].

**Bio-sensors**

Sensors to monitor the heart rate are employed to predict physical activity [41], [42], [43]. Popular in health related applications is also the monitoring of blood pressure [44] or electrocardiographony ECG [45], [46]. In addition, Electromyography (EMG) sensors are used to monitor the health status [47] or, e.g. facial EMG to support eye-gaze tracking sensors [48]. This sensor class is feasible to record muscle activity (surface EMG electrodes) [49], [50].

**RF-based**

Device localisation is possible by employing WiFi signal strength and signal-to-noise-ratio [51], [52], or also via signal strength information of a set of signals received from nearby FM radio stations [53], [54].

Device-free

**Installation-based**

- **Video**
  
  Recognition of activities from video can reach remarkable accuracies [55]. Activities are identified via matching of templates, neighbour based or via statistic modelling [56], [57]. However, video has high installation cost, is strictly range limited, fails in darkness and may violate privacy.

- **Infrared**
  
  Capturing of radiated infrared waves emitted from objects, infrared can be employed as imaging technology similar to video but with the benefit that human motion can be easily detected from the background regardless of the lighting conditions and colors of the human clothing and surfaces [58], [59]. The technique is limited in sensing range and requires careful and dense deployment.

- **Pressure**
  
  Pressure sensors typically exploit the change of conductivity due to deformation or expanding of wires and can be integrated in fiber of textiles [60], [61]. They are utilised to track footsteps and locations of individuals as well as touch-interaction with the environment [62]. Installation cost is typically high and requires careful deployment.

- **Ultrasound**
  
  Ultrasound can indicate relative location of a pair of devices via Time-Of-Flight (TOF) [63]. Accuracy can be improved via combination with radio frequency [64].

- **Depth camera**
  
  Equipped with a depth camera and capable of voice interaction, the Kinect device is able to accurately track gestures of persons [65], [66] and interaction [67].

**Infrastructure-mediated**

- **Exploitation of alternative sensing modalities which are pre-installed and readily available in environments and therefore minimise installation cost.**
  - **Resistance; inductive electrical load**
    
    Alterations in resistance and inductive electrical load in a residential power supply system can be exploited to detect human interaction in a building [68]. Authors leveraged transients generated by mechanically switched motor loads to detect and classify human interaction from electrical events.
  - **Electromagnetic interference (EMI)**
    
    Gupta et al. analysed electromagnetic interference (EMI) from switched mode power supplies (SMPS) in order to detect human interaction with electrical systems [69]. It is even possible to detect proximity of the human body towards a fluorescent lamp. Utilizes from the change in impedance in the EMI structures [70].
  - **Water pressure**
    
    Leveraging residential water pipes, the change in water-pressure within the pipe system can be utilised to classify water-related activities and their location in the house (flushing toilet, washing hands, showering,...) [71], [72], [73].
  - **Gas consumption**
    
    With a single sensing point, gas use can be identified down to its source (e.g., water heater, furnace, fireplace) [74]. The authors monitor the gas-flow via a microphone sensor.
  - **Electromagnetic noise**
    
    Using electrostatic discharges from humans touching environmental structure, it is possible to detect locations that have been touched and gestures from electromagnetic noise [75], [76].

**Environmental / Parasitic**

- **Audio**
  
  Audio can be utilised to identify the location of a phone on room-level and also various in-room (e.g. on table, in drawer) or on-body locations (e.g. pocket) [77]. Furthermore, audio-fingerprints can serve as a sense of proximity among devices [78].

  - **Radio frequency**
    
    Passive Radar describes a class of radar systems that detect and track objects (vehicles, individuals) by processing reflections from non-cooperative sources of illumination in the environment, such as commercial broadcast and communications signals (HF radio, UHF TV, DAB, DVB, GSM) [79], [80]. In these systems, no dedicated transmitter is involved but the receiver uses third-party transmitters. It then measures the time difference of arrival between Line-of-Sight (LoS) signals and signals reflected from an object. By this it is possible to determine the bistatic range of an object and its heading and speed via Doppler Shift and its direction of arrival. Expensive systems can operate in ranges of several 100 km but are very expensive.

  - **Recognition of movement is also possible with simpler hardware (WiFi, Sensor nodes, Software-defined-radio) considering the interception of LoS paths between pairs of nodes [79]. In addition, highly accurate localisation was demonstrated by extracting the LoS components among a grid of nodes [80]. Furthermore, it is possible with similar installations to distinguish activities and gestures (via Doppler fluctuations) [81], [82].

This limitation is relaxed by systems that utilise environmental sources, such as radio frequency (RF) or audio [79], [23].

In the present survey, we focus on most recent developments in radio-based device-free-recognition. Such systems monitor changes observed on the RF-channel and analyse them for characteristic patterns. Changes in the location of objects or movement of individuals causes variation in the radio channel characteristics. For instance, due to blocked, damped or reflected paths of some of the signals superimposed at a receive node, the absolute signal strength might differ. Also, movement might induce Doppler shift in reflected signals and thus lead to changes in the distribution of energy over frequency bands at the receiver. Figure 4 summarises relevant radio effects that can be exploited for environmental awareness from received RF signals.

An early example of a system utilising WiFi signals for the localisation of a receive device is the RADAR system that employed signal strength and signal-to-noise-ratio (SNR) from WiFi [59]. Other implementations utilised GSM for localisation by employing signal strength readings from the active set [51], [52] or signal strength from a set of FM base stations [53], [54]. Frequently, these approaches require the creation of a received signal strength (RSS) fingerprint map [59], [90], [91], but also real-time on-line localisation that does not require a fingerprinting map is feasible [92], [93], [12], [94], [13]. The latter approaches combine, for instance, dead reckoning methods with characteristic, crowd identified, waypoints for accurate relative localisation. These systems are device-bound and can reach high accuracy of about 1 meter [95].

For device-free approaches, on the other hand, the mon-
Fig. 5. RF-based device-free activity recognition systems and their recognition capabilities and system configuration considered. The figure groups related the corresponding reference to reach system under the respective class.

The monitored entity is not equipped with any transmit or receive device [79]. We distinguish between four classes of such recognition systems conditioned on their hardware configuration (cf. figure 5). These systems can be grouped into active and passive approaches conditioned on the presence of an active transmitter [96]. Active systems control both, transmit and receive hardware while passive systems only utilise receive devices. Most current systems are active such that both, the receiver and the transmitter are under the control of the system. Generally, the classification accuracy of an RF-based device-free recognition system suffers when the transmitter is third-party controlled.

Many early studies utilise continuous signals captured by Software-Defined Radio (SDR) devices for their more accurate and complete access to the radio channel. These systems can exploit continuous signals received on the wireless channel and sampled at a high frequency, which enables the utilisation of frequency domain features.

In contrast, consumer devices seldom feature SDR-capabilities. On such devices, frequently, the Received Signal Strength Indicator (RSSI) is exploited as an indicator for surrounding activities and situations.

Figure 5 indicates research achievements demonstrated for the respective classes and system configurations by various groups. Most results have yet been achieved for active, continuous signal based systems. On the contrary, passive RSSI-based systems are only recently considered. In addition, most work considers the recognition or localisation of individuals (presence, location). For continuous signal-based systems also more complex cases like activities have been considered. More complex system configurations or classes are to-day less frequently investigated and partly also constitute open research questions.

The following sections detail the research conducted in these fields in more detail and also cover comparative measures like accuracy of recognition.

A. Localisation

Device-free RF-based recognition was first investigated for the task of localisation or tracking of an individual. Youssef defines this approach as Device-Free Localisation (DFL) in [79] to localise or track a person using RF-Signals while the entity monitored is not required to carry an active transmitter or receiver.

In the following, we distinguish between preliminary studies considering basic impacts of presence and movement on a received radio signal, radio tomographic imaging approaches, RF-fingerprinting methods, anomaly detection methods and approaches that isolate direct links among nodes in order to analyse their fluctuation.

1) Impact of presence and movement: Youssef et al. analysed the impact of presence on a received radio signal and defined three tasks for DFL: detection of presence, tracking of persons and predicting identity of individuals [79]. For the mere detection of presence, they analysed the moving variance and moving average of the time-domain signal strength of RSSI values from transmitting and receiving pairs of WiFi devices (access points (AP) and mobile terminals). Classification accuracy reached up to 1.0 for some configurations. In
order to track individuals they proposed the use of a passive radio map (see section II-A4).

Kosba et al. presented in [97] a similar system to detect motion from RF-readings of standard WiFi hardware. Their system utilises a short offline training phase in which no movement and activity is assumed as a baseline. Then, anomaly detection is employed in order to detect changes from that baseline. The authors considered mean or variance-related features and concluded that the variance is better suited to detect changes in the RSSI. In contrast to the works of Zhang and others, this system does not require WiFi nodes to be located in an exactly defined grid with fixed node distances. Consequently, localisation is not possible but mere detection of presence.

Also, Lee et al. consider the utilisation of RSSI fluctuation from pairs of communicating TelosB nodes for intrusion detection [98]. In five distinct environments (outdoor and indoor) they reported changes in the mean and standard deviation of absolute RSSI values.

Utilising a passive, FM-radio based system with SDR devices, Popleteev indicated that frequency diversity can help to improve localisation accuracy of RF-based systems [99]. In particular, he considered a person located at 5 different locations inside a room and predicted the location with a standard k-nearest neighbour approach. In addition, the author pointed out that the classification accuracy of the system would deteriorate when the system is trained on one day but classification is conducted on another day.

Lieckfeldt and others considered the impact of the presence of a single individual on the received signal strength observed by an RFID reader in a 2m×2m area equipped with 69 passive RFID tags [100]. Their system utilised a two-staged approach in which first the RSSI fluctuation without presence was recorded and later, presence was detected via the observed changes in the signal strength from the set of tags. The authors observed that the backward link is more expressive for the recognition of presence than the forward link from the reader. In addition they considered different orientations of the monitored individual in order to arrive at more general results.

2) Radio tomographic imaging: Tomography describes the visualisation of objects via a penetrating wave. An image is then created by analysing the received wave or its reflections from objects. A detailed introduction to obstacle mapping based on wireless measurements is given in [101, 102]. Radio tomography was, for instance, exploited by Wilson et al. in order to locate persons through walls in a room [103]. In their system, they exploit variance on the RSSI at 34 nodes that circle an area in order to locate movement inside that area. Nodes in their system implement a simple token-passing protocol to synchronise successive transmissions of nodes. These transmitted signals are received and analysed by the other nodes in order to generate the tomographic image by heavily relying on Kalman filters. They were able to distinguish a vacant area from the area with a person standing and a person moving. In addition, it was possible to identify the location of objects and to track the path taken by a person walking at moderate speed. An individual image is taken over windows of 10 seconds each. By utilising the two-way RSSI fluctuations among nodes, an average localisation error of 0.5 meters was reached [104].

It was reported in [105] that the localisation accuracy of such a system can be greatly improved by slightly changing the location of sensors, thus exploiting physical diversity. The authors present a system in which nodes are attached to disks equipped with motors in their center for rotation as depicted in figure 6. With this setting it is possible to iteratively learn a best configuration (physical location) of nodes similar to, for instance, iterative beamforming approaches that try to lock several radio signals on the optimal relative phase offset [106, 107].

Wagner et al. implemented a radio tomographic imaging system with passive RFID nodes instead of sensor nodes. Implementing generally the same approach as described above, they could achieve good localisation performance with their system. However, they had to implement a suitable scheduling of the probabilistically scattered transmissions of nodes due to the less controllable behaviour of passive RFID nodes [108]. In later implementations, they improved their system to allow on-
line tracking [109] and a faster iterative clustering approach to further speed up the time to the first image generated [110]. This image is then of rather low accuracy but is iteratively improved in later steps of the algorithm. With this approach, it was possible to achieve a localisation error of about 1.4m after only one second and reach a localisation error of 0.5m after a total of about seven seconds in a 3.5m$^2$ area.

Utilising moving transmit and receive nodes and compressive sensing theory [111], [112], [113] it is possible to greatly reduce the number of nodes required. For instance, Gonzalez-Ruiz et al. consider mobile robotic nodes that mount transmit and receive devices and circle the monitored target in order to generate the tomographic image [114]. In particular, they required only two moving robots attached with rotating angular antennas in order to accurately detect objects in the monitored area. Each robot takes new measurements every two centimeters. Overall, after about 10 seconds a single image can be taken. They detail their implemented framework in [115] and the theoretical framework for the mapping of obstacles, including occluded ones, in a robotic cooperative network, based on a small number of wireless channel measurements in [116].

3) Machine learning: Instead of generating radio-tomographic images, which is an accurate but comparatively slow procedure, also general Machine Learning approaches can be employed for RF-based localisation. For instance, Wagner et al. investigate the localisation in a passive RFID setting utilising multi layered perceptrons for training-based device-free user localization [117]. In particular, the authors utilised a three-layer neural network that takes the a series of measurements as input vector and provides a tuple as output defining a two-dimensional user location. Localisation error achieved could be kept below 0.5 meters in a 3m$\times$3m square area.

4) RF-Fingerprinting: A common approach to RF-based localisation is the construction of radio strength maps. In device-based systems, RSS at various locations is tracked and used as a map together with access point IDs [118]. With this information, location is later estimated from life measurements. Such radio maps may also be deployed with device-free systems in which the RSSI fluctuations in the presence of a person not equipped with a transmit or receive device are captured. Youssef et al. present such a localisation system in [79]. They report that the RSSI is more stable over night when no people are around so that this is the best time to create an RSSI fingerprint map. In a system with two transmit and two receive WiFi devices monitoring the RSSI in infrastructure mode from beacons sent roughly every 100ms they have been able to accurately predict and trac location of a single person in an indoor location. Later, they improved their approach using less nodes [119]. This was possible by employing a Bayesian inference algorithm. All these experiments have been conducted under Line-of-Sight (LoS) conditions. A major drawback has been the time-consuming manual generation of the fingerprint maps, however, with current systems, also automated generation of RSSI fingerprints on laptop-class computers is possible [120].

5) Geometric models and estimation techniques: Finally, in systems where the relative location of nodes that transmit and receive signals is exactly known, the geometry and layout of the instrumentation can be exploited. Zhang et al. employed a grid of nodes in order to localise individuals from device-free WiFi readings [121]. They proposed a straightforward theoretic model to describe signal fluctuation induced by passive objects and verified their findings in a case study with ceiling mounted MICA2 sensor nodes transmitting with 0dBm at 870MHz. The three algorithms proposed (Midpoint, Intersection, Best cover) all require an initial training phase in which the RF fluctuation is monitored in a stable state with no interference through individuals (cf. Frequency Selection Algorithm in figure [7]). All algorithms utilise knowledge about the relative location of nodes and exploit RF-signal strength fluctuation on direct links. From this, center locations on the direct links, Intersections of direct links or 0.5$\times$0.5m$^2$ areas on the direct links are utilised in order to predict the location of activity. Best results have been achieved with the consideration of overlapping areas. The optimum distance among two nodes...
in the grid has been experimentally derived as 2 meters. With this configuration, a single person moving slowly (0.5 m/s) along a straight line has been tracked with an accuracy of below 1m and two persons with an accuracy of below 2m. With additional clustering of nodes, the accuracy for the tracking of multiple persons could be further improved to slightly more than 1m [122]. Also, the transmission power was demonstrated to impact the tracking accuracy and lower transmission powers of −6 to −11 dBm have been observed to show more dynamic values for short node distances. The system was shown to be real-time capable in [80]. By clustering the measurement area into several, frequency-separated cells, spanned by three nodes each, the authors could isolate interference from neighbouring nodes and also speed up the computation (cf. figure 7).

Utilising passive RFID transponders, Lieckfeldt et al. exploited device-free Localization in recent years [123], [124]. The authors propose a physical model that depicts the effect of relative position of subjects on the signal strength. They propose estimators for user localization, based, for instance, on maximum likelihood and geometric methods, such as nearest intersection points. While the geometric approaches suffer from a low accuracy, the estimation based methods are characterised by a high computational complexity.

A straightforward approach to localisation based on RSSI fluctuation is the consideration of the interception of LoS paths in a grid of nodes. A first step in this direction was taken by Patwari et al. who derived a statistical model for the RSS variance as a function of the location of a single individual [125]. They could show that reflection causes the RSS variance contours to be shaped approximately like Cassini ovals. They also considered the simultaneous localisation of multiple individuals at the same time and argue that their model could be extended to cover multiple individuals. This was later demonstrated to be feasible in an actual system instrumentation by Zhang and others [126]. 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 5 persons in a changing environment with an accuracy of 1 meter.

B. Recognition of activities

Not only static location but also activities, gestures or situation in proximity of a receive antenna can be distinguished from signal fluctuation over time. For RF-based activity recognition, a higher sampling frequency is required than for mere localisation or tracking. Depending on the specific application, sampling rates between 4Hz and 70Hz are utilised. Consequently, methods such as tomographic imaging are too slow to achieve reasonable accuracy here. Furthermore, as location is not the main interest, geometric models and RF-fingerprinting are not employed. Especially the latter captures static situations and can therefore not be applied for the recognition of dynamic changes over a time window.

Instead, machine learning techniques are frequently applied to analyse fluctuation in signal strength measurements over time. In addition to RSS, also movement-indicating features such as frequency-domain features or Doppler shift are exploited.

1) Machine learning and estimation: In their seminal work, Patwari et al. report that they are able to detect the breathing rate of a single individual by analysing the RSS fluctuation in received packets from 20 nodes surrounding the subject [83]. Via maximum likelihood estimation, they were able to estimate the breathing rate with a Root-Mean-Square-Error (RMSE) of 0.3 breaths per minute. Their system consists of Telos B nodes transmitting every 240ms on a center frequency of 2.48 GHz, which translates to an overall packet transmission rate of about 4.16Hz. Prediction was taken after a 10 second to 60 second measurement period. Best results could be achieved with 25 to 40 seconds whereas longer observation periods did not further improve the accuracy significantly. Naturally, the accuracy achieved was dependent on the number of nodes that participated. While a single node pair could not achieve usable results, already with 7 network nodes, an RMSE breathing rate error of only about 1.0 was observed. They could further show that the links with low average RSS are most significant for the detection of breathing rate.

With standard machine learning approaches (e.g. k-nearest neighbour, decision tree, Bayes, support vector machines), it is possible to extract further information on environmental situation from RSS fluctuation. In preliminary studies, Reschke, Scholl, Sigg and others demonstrated the detection of opened or closed doors, presence and crowd size with an accuracy of 0.6 to 0.7 [128], [129], [127], [130] (figure 8 illustrates the SenseWaves recognition system for the distinction of three
fairly separated classes).

The authors utilised USRP Software defined radio devices (SDR)\(^2\) from which one constantly transmits a signal at frequencies between 900MHz to 2.4GHz that is read and analysed by other nodes. The SDR devices allow high sampling rates of the observed signal. In their system, the authors employ sampling rates of 40Hz from a continuous signal transmitted by one node. No specific relative placement of nodes was required so that the system qualifies for ad-hoc deployment. For recognition, simple time-domain RSS features such as the Root of the Mean Squared (RMS), Average Magnitude Squared (AMS), Signal-to-Noise Ratio (SNR)\(^{[128,129,130]}\), signal amplitude, signal peaks in a defined time period and the number of large deltas in successive signal peaks\(^{[127]}\) have been utilised. Also, the consideration of crowd size extends the often followed single-individual sensing approach\(^ {131}\). The author’s learning approach is able to predict the count of up to 10 stationary or moving individuals.

Later, with the consideration of additional and also frequency domain features, recognition accuracy was further improved\(^ {132,133}\). In addition, the authors compared several device-free recognition techniques and also accelerometer-based recognition with the result that the active and passive device-free and continuous signal based systems could score similar results as accelerometer-based recognition systems. The authors also reported that some features such as the variance are robust against static environmental changes for the detection of dynamic activities, such as walking or crawling. In addition, it was possible to distinguish activities conducted by multiple persons simultaneously in an active SDR-based system. With two persons conducting activities at two locations and four receive devices, the authors trained the classifiers on the combined features and could distinguish 25 cases with high accuracy\(^ {134}\) (cf. figure 9). Later, the recognition of gestures in the proximity of a receive antenna was reported with a similar approach\(^ {135}\).

In a related work with an SDR-based but passive system, Shi et al. exploited signals from a nearby FM radio station for the detection of activities. Their method also exploits machine learning approaches but relies more on frequency domain features. In addition, their sampling rate is lower with about 2Hz and a sampling window of 0.5 seconds\(^ {136,137,138}\). However, the accuracy achieved is comparable to the above active systems.

Another approach utilising RSSI information from sensor nodes in an active RSSI-based system was presented in\(^ {139}\). The authors place eight 802.15.4 nodes that transmit at 2.4GHz in a 20m\(^2\) office room. The nodes were placed at various heights from 30cm to 1.4m. With this setting and only mean and variance as features, the authors could distinguish seven different classes at an accuracy that exceeded the accuracy achieved by an accelerometer attached to the subject for comparison. They reported that their 3D topology helps to distinguish activities and that there are indications that discrimination of subjects might also be possible.

\(^2\)http://www.ettus.com

Very recently, Sigg et al. investigated the distinction of gestures and situations in a passive device-free system with only one off-the-shelf (smartphone) receiver\(^ {140,142}\). They observed that 10 RSSI packets per second could be expected in urban places and that these are sufficient to distinguish between simple classes and also hand gestures in proximity of the receiver. Although their accuracy reached was lower than for the active RSSI-based system reported above, it was clearly above random guess. In addition they could distinguish 11 gestures performed in close proximity of the phone.

2) Doppler Shift: When an object reflecting a signal wave is in motion, this causes Doppler Shift. The direction and speed of the movement conditions the strength and nature of this frequency shift. Pu and others showed that simultaneous detection of gestures from multiple individuals is possible by utilising multi-antenna nodes and micro Doppler fluctuations\(^ {2,141}\). They utilise a USRP SDR multi-antenna receiver and one or more single antenna transmitters distributed in the environment to distinguish between a set of 9 gestures with an average accuracy of 0.94. Their active device-free system exploits a MIMO receiver in order to recognise gestures from different persons present at the same time. By leveraging a preamble gesture pattern, the receiver estimates the MIMO channel that maximises the reflections of the desired user.

A main challenge was for them that the Doppler shift from human movement was several magnitudes smaller than the bandwidth of the signal employed. The authors therefore proposed to transform the received signal into several narrowband pulses which are then analysed for possible Doppler fluctuation. The group discussed application possibilities of their system in\(^ {142}\).

In a related system, Adib and Katabi employ MIMO interference nulling and combine samples taken over time to achieve a similar result while compensating for the missing
spatial diversity in a single-antenna receiver system. In their system, they leverage standard WiFi hardware at 2.4GHz.

Later, this work was extended to 3D motion tracking by utilising three or more directional receive antennas in exactly defined relative orientation. In particular, the system is able to track the center of a human body with an error below 21cm in any direction and can also detect movement of body parts and directions of a pointing body part, such as a hand. This localisation is possible through time-of-flight estimation and triangulation. Higher accuracy of this estimation is granted by utilising frequency modulated carrier waves (sending a signal that changes linearly in frequency with time) over a bandwidth of 1.69GHz. Impact of static objects could be mitigated by subtracting successive sample means whereas noise was filtered by its speed of changes in energy over frequency bands.

IV. TOWARD COGNITIVE ACTIVITY RECOGNITION

Physical activity tracking came a long way, from dedicated sensing devices in lab settings to consumer applications embedded in wearable appliances (e.g. Fitbit, Jawbone UP) and even dedicated human motion tracking co-processors in smart phones (e.g. M7 in the iPhone 5s). Now we are seeing the first end consumer devices that start exploring our physiological signals (heart rate, blood oxygen level etc.) and our sleep performance.

The next logical step is the tracking of cognitive activities: attention, recall, cognitive load and finally learning and decision making. We explore in this section which sensor modalities seem to have the most merit and then tackle a very specific type of cognitive task, namely reading. We discuss why reading is a good choice to start with and how we tracking can be extended towards other cognitive activities.

A. Importance of Eye Gaze

The most obvious way to track cognitive tasks is to monitor the brain directly. Although this approach sounds promising, there are a lot of practical problems with direct brain monitoring. Either the methods are very obtrusive (e.g. fMIR) or they have problems with noise, movement artifacts and are not easy to wear during everyday life.

As intermediate technology, eye movement tracking seems to be the most promising. As it can be easily monitored either using optical eye tracking or electrooculography (electrodes placed close to the eye). Also, eye movements are closely correlated to cognitive activities and states. From simple blink frequency analysis that can tell you about the fatigue of a user to expertise analysis for complex visualizations.

B. Quantifying Reading Habits

In this section, we focus on tracking reading as a cognitive activity. There are two main reasons. First, reading is a ubiquitous task, performed everyday crucial to our learning and knowledge acquisition. Although there are very detailed studies of reading activities in the lab, there are very few in-situ studies about reading behavior in real life. Second, we believe “reading” can become to cognitive activity tracking what “walking” and locomotion analysis became for the physical task tracking. Reading analogous to Walking is easy to define and includes repetitive movements with distinct frequencies. This should make the task of spotting it easier, while preventing the definition problem. Take ”focusing” or "paying attention" as an example, for spotting cognitive activities depends highly on how you define them.

To track reading habits we evaluated a couple of technologies (e.g. EEG, eye tracking, motion sensors, egocentric cameras) and found mobile eyetrackers are so far the best suited for the task (see Fig. 11 for an exemplary setting with a person wearing a mobile eyetracker). Our analysis goes from simple word count over reading material inference to trying to assess reading comprehension.

1) Word Count and Reading Speed: It is possible to implement a wordometer using optical mobile eye tracking. The number of words a user reads can be counted by recognizing reading, counting line breaks and then approximating the words read. Current implementations works with an error rate of around 6-11% for 10 users over 20 documents with sizes ranging from 150-680 words.
The recognition process works as follows. First, reading is recognized by a support vector machine using fixation and saccade features [144]. Afterwards, there are several ways to estimate reading volume: using time only, detecting a line break (long saccade back towards a new line) to estimate lines, based on the lines or the word count. The latter method works better (5-15% lower error rate).

Reading volume in itself is associated with an increase in vocabulary and there are strong correlations between size of vocabulary and language skill. However, more interestingly, reading volume seems also an indicator for higher general knowledge [145]. In itself, reading volume is therefore already interesting information. Yet, it can also enable novel applications, like annotating books with the amount of reading a user did (and at which pages) to give feedback to authors.

2) Document Type Classification: Using also a mobile eyetracker, it is possible to tell which documents a user reads. In figure 12 exemplary eye-gaze patterns are displayed for various document types (comic book, text book, magazine etc.). In an experiment with 10 users reading 5 different document types for 10 minutes in 5 different environments (e.g. office, coffee shop) an accuracy of 78% for around 1 minute windows are achieved independent of the user and 98% for the user dependent case. As long as the document layout is sufficiently unique, information about the document is also contained in the eye movement [146].

This raises the interesting question, if given a particular goal, there are optimal eye gaze patterns for reading a particular document. If this were the case, we could store the optimal eye gaze pattern and adjust the document accordingly if the user deviates from that pattern.

3) Toward Reading Comprehension: In the same line of research yet even more difficult, researchers assess whether it is possible to estimate expertise level from eye gaze.

So far, the results are ambiguous regarding the estimation of reading comprehension. Although there is a clear correlation between a couple of eye gaze features and the comprehension of the reader, the data seems noisy making a good inference difficult. We can detect difficult words by using fixation counts for individual users, yet so far it was not possible to determine reading comprehension directly [28]. Difficult word detection is based on fixation count. Difficult words have a statistically significant increase in fixations.

C. Augmenting Reading

As a first step to explore reading comprehension more, it is evaluated if and how implicit text annotations using eye gaze can support second language learners and their teachers. Starting with giving readers quantified feedback about their behavior, answering simple quantitative questions: How fast do they read a paragraph? How much re-reading do they do? Yet, finally the aim is to give the reader feedback about their concentration and finally text comprehension level.

The current focus is set on paragraph based annotations, as these already can give valuable support to the learner and are feasible to implement with current technology. The initial set of annotations are inspired by lab internal discussions and by related work [147].

In a prototype implementation, reading speed is highlighted by background color and intensity. Slow speed with darker hue, faster speed with lighter hue. Reading speed is given by how long the participants eye gaze is in a paragraph region.

The amount of re-reading is estimated by comparing the line count of the paragraph with estimating the line count by using eye gaze using a method from Kunze et al. [148]. The amount of re-reading is shown by an arrow pointing back up (cf. figure 13).

Fixations are aggregated in larger fixation areas applying a filtering method from Busher et al. [147]. The number of fixation areas are shown as a eye icon next to the paragraph.

In Figure 13 we depict these annotations for a document read by students with good and poor English skills. The good student performs less re-reading and has in general a fast reading speed. Although the differences between the two participants are easy to see, eye gaze is not only influenced by our expertise level, but also from fatigue and other mental states. Therefore, it’s difficult to give comprehensive evaluations. Moving away from reading, we can also use cognitive activity recognition for implicitly tagging objects and events.

D. Cognitive Tracking for the Masses

A major problem of studies on cognitive activity recognition is that it is very difficult to make them representative, as sample sizes are relatively small (10 - 20 participants). Problems also cover the activity recognition field in large and other information technology fields addressed. Dealing with cognitive tasks, this however is of additional weight. As seen from similar cognitive science and psychology studies, very large sample sizes are needed to assess the relations between tasks and cognitive activities, especially related with complex processes like learning.

One way to approach this problem is to provide affordable commodity devices to enable contributions from people towards the questions of intelligence amplification.

As eye trackers are still expensive and some people might not want to wear glasses, we should focus on alternative technologies that are already available or can be easily integrated into consumer devices, to enable cognitive task tracking.

Additionally, head-mounted display computers, most prominently Google Glass, seem to get more and more commercial attention. They are a perfect tool for cognitive task analysis, as they are already worn on the head. A very simple sensor (infrared distance sensor from Google Glass) can for example measure eye blinks. Astonishingly, blinking frequency alone is already able to distinguish a couple of cognitive tasks (e.g. Reading versus Talking to a person, see Fig. 14 [150].

V. DISCUSSION AND FUTURE DIRECTIONS

Activity recognition will increasingly focus on Parasitic and Sentiment Sensing paradigms. For device-free RF-based recognition, we expect that the diversity of sensors on devices can be greatly reduced as RF- and other environmental sources are capable to replace more specialised sensors with acceptable accuracy. This will result in a simpler and thus cheaper design.
Fig. 12. Examples for different eye gaze patterns for varying document types (Textbook, novel, magazine, newspaper, manga)

Fig. 13. Eye-gaze annotated document for a participant with low English skills (first four paragraphs) and higher skills (second four paragraphs). First we show the raw eyegaze as recorded by the eyetracker, then the annotated document. Shading shows the reading speed: the darker the slower. The arrows on the right show the amount of re-reading and the size of the eye next to the paragraph the number of fixation areas.

Nature photographer Stan Lynch will be speaking about his award-winning new book at the City Library on Thursday, March 12. This event promises to be fascinating for both photographers and lovers of photography.

Lynch's new book is a departure from all his previous work. He has only published books of photography in the past, but his new offering, You Could Do This, is basically a how-to guide for anyone who wants to take better photos. For a photographer who has won every major award to write an instructional guide is highly unusual, and the result is utterly compelling.

Mr. Lynch will be covering some of the key concepts from his book during this special seminar, including composition, light and editing. He will also be answering questions and no doubt telling many of his famous stories from decades of shooting pictures in the wild.

Tickets are available from February 10 through the Library Foundation or on the Library website. A limited number of tickets will be available at the door, so it's best to make sure you get yours ahead of time. Library Foundation members get a 20-percent discount, limited to two tickets, only if purchased in advance.
of consumer appliances with more accurate specialised sensing hardware reserved for professional devices.

Sentiment Sensing will receive considerable attention over the course of the next couple of years. The knowledge on mental states will breed a number of new applications and challenges.

In addition, we expect that these sensing paradigms will increasingly be applied on non-expert off-the-shelf consumer hardware. This development will foster a wide adaptation of these sensing paradigms and enable a number of novel applications as well as revenue for companies.

A. Environmental conditions

Since parasitic sensing exploits environmental sensing sources, it is suggestive to monitor environmental conditions with such signals. The sensing of traffic situations from environmental parasitic sources is gaining increased attention and might be fuelled also by vehicular communication, autonomous driving and pedestrian safety campaigns. But also other measures like, for instance, temperature can be sensed parasitically from RF.

1) Temperature: As detailed in [151], the outside temperature impairs the capability of WiFi equipment, which might greatly reduce its transmission range. By inversion of the same argument, the range of WiFi equipment will allow conclusions on the surrounding temperature. While it is difficult to estimate the distance between a WiFi access point (AP) and a wireless receiver directly, utilising changes in signal strength information from multiple APs should enable accurate prediction of environmental temperature.

2) Sensing traffic situations: Electromagnetic emission can be detected from a number of entities, including car engines. Regulation by EMC requires that emission from combustion engines fulfills strict requirements in the 30-1000 MHz range [152]. But also for alternative power train road vehicles similar requirements apply. [152]. These emissions are tested with standardized radiated emission tests such as CISPR 12 [153] or CISPR 22 [154].

In [155] it has been shown how RF emission from car’s engines can be utilised in order to detect various car models. The authors have been able to distinguish between three car models with an accuracy of 0.99 with the help of an Artificial Neural Network-based classifier. For this, the ignition spark was the most characteristic event. The characteristic features were identified over a frequency range of 2.5 GHz.

Kassem et al. [156] sense traffic situations by tracking frequency and speed of passing cars that intercept the direct line of sight between a pair of nodes on both sides of the road. Furthermore, Ding et al. demonstrated, how emissions from car engines can be utilised for passive traffic awareness utilising either roadside installations or also in-car modules [81], [157]. The authors have employed standard machine learning approaches in order to distinguish six traffic situations from roadside measurements and, in addition, the own-vehicle’s speed with in-car measurements. Recognition accuracy achieved in realistic environments were above 0.96 in all cases. Possible further applications include the detection of traffic jams or also the number of cars waiting in front of a traffic light.

B. Sentiment and mental states

As detailed above, sentiment and mental states are on the verge to be recognised from environmental and on-body sensors.

1) Emotion: Emotion can be inferred from body gesture and pose [9] at least as accurately as from face [158], [159], [160]. The role of human body in emotion expression has received support through evidences from psychology [161] and nonverbal communication [162]. The importance of bodily expression has also been confirmed for emotion detection [163], [164], [165].

Walter and Walk [161] revealed that emotion recognition from photos of postural expression, in which faces and hands were covered, was as accurate as recognition from facial expression alone. Dynamic configurations of human body even hold greater amount of information as indicated by Bull in [166]. He proved that body positions and motions could be recognized in terms of states including interest/boredom and
agreement/disagreement. Some other studies went further by looking for the contribution of separated body parts to particular emotional states [167], [168]. Emotion can be recognized from non-trivial scenarios, such as simple daily-life actions [169], [170] or recognition ability of infants [171].

It will be interesting to see how well RF information can be exploited in order to identify body gesture and pose and to classify this for human emotion classes.

2) Attention: Attention is an important measure in Computer-Human interaction. It determines for an interactive system the potential to impact the actions and decisions taken by an individual [172]. The same action of the same system might be considered either as annoyance or be appreciated as helpful depending on whether the individual was focusing part or all of her attention towards the system or not. In the literature, we find various definitions that classify attention as well as its determining characteristics [173], [174]. While the tracking of gaze is a commonly utilised measure of attention [175], also other observable features may indicate attention. In general, aspects such as Saliency, Effort, Expectancy and Value are important indicators of attention [176], [174]. [173]. This model was later extended to put a greater stress on the effort a person takes towards an object [178]. The authors also discuss various aspects of attention and identify as most distinguishing factors changes in walking speed, direction or orientation.

In [24] it was investigated, how these properties, in particular location of a person, walking direction and walking speed or changes therein can be utilised for the monitoring and detection of attention. This was yet a preliminary study which lacked generalisation and high accuracy but we will see further improvements of attention recognition via RF soon.

C. Enhancing Recall and Focus

Successfully tracking tasks, like emotion or attention enables us to improve our cognitive abilities. The ultimate goal of research conducted in these directions is to improve memory, concentration and finally decision making.

If we can track attention levels and cognitive load, we can identify the best times for the user to relax, learn, study or engage in spare-time activities, depending on their current cognitive state.

D. Device-free RF-based recognition on consumer hardware

Currently, RF-based device-free recognition from continuous-signal based devices (such as e.g. SDR-nodes) can be considered as solved. Future directions are towards the recognition on consumer devices. With the introduction of OFDM to many wifi-class devices, some of the features, of SDR nodes, such as utilisation of multipath information can be incorporated from OFDM channel state information. For WiFi-based indoor localisation, this has already been employed recently to achieve sub-meter accuracy [179]. In contrast to RSSI, the CSI contains channel response information as a PHY layer power feature [180]. Therefore, it becomes possible to discriminate multipath characteristics which hold the potential for more accurate classification of activities from RF. The utilisation of channel response was before recently only possible with sophisticated SDR hardware [181], [182], [183]. With introduction of Orthogonal Frequency Division Multiplexing (OFDM) for WiFi 802.11 a/g/n standards, this has, the channel response can now partially be extracted from off-the-shelf OFDM receivers, revealing amplitudes and phases of each subcarrier [184]. While RSSI is not able to capture the multipath effects in an environment, as depicted in figure 15 the channel response available via CSI possesses finer grained frequency resolution and higher time resolution to distinguish multipath components.

Apart from this straightforward future research direction (which is already approached to-date by several groups), we can identify also more specific open research questions as follows.

1) Empowering WiFi access points: Authors have demonstrated the detection of several situations (for instance presence or crowd size) from RSSI information on a mobile phone [24]. More interesting even is the estimation of crowd size or presence at a WiFi AP. At the access point, the incoming packets originate from multiple devices at multiple locations. In addition, traffic from an individual mobile device is typically much lower than the traffic generated by an AP. It is not a-priori clear whether the snippets of RSSI-samples from distinct mobile devices are sufficient to estimate classes like crowd size or presence at a WiFi AP. In particular, analysis of the evolution and fluctuation of the average RSSI level as well as normalisation of incoming flows regarding their signal strength might help to acquire such information.

2) Activity recognition from 3G and 4G signals: In [24] it was demonstrated how RSSI information from WiFi traffic can be utilised to identify environmental situations and gestures conducted in the proximity of a WiFi receiver. Similarly, it will be possible to utilise 3G or 4G signals for the distinction of similar classes. For this, however, the first step is the modification of the firmware for the 3G or 4G interface to allow access to signal strength information at higher frequency as this was done for the WiFi interface in [24].
In this survey we have discussed recent advances in activity recognition which are leading towards two emerging sensing paradigms, namely Parasitic Sensing and Sentiment Sensing. Both are fostered by the extreme increase in sensing devices in people’s environments. While classical sensing on mobile devices covers the surface of an individual’s actions, namely her directly observable conditions, actions, movement and gestures, future sensing paradigms extend the reach of a device’s perception. Parasitic Sensing utilises noise of environmental, pre-installed systems and thereby captures stimuli from a device’s near to mid-distance surroundings. On the other hand, sentiment Sensing reaches inwards, focusing on mental state and sentiment. We see great potential for novel applications and revenue in both these paradigms.

Parasitic Sensing is fostered by the rise of the Internet of Things which will deploy a multitude of sensing and communicating devices in the environment. In particular, these devices will feature an interface to the RF-channel which is why we envision this as the one universally employed sensor on such devices. Apart from the already existing RF-noise to-day, IoT devices will generate significant additional traffic on such devices. This will open new insights for activity recognition in smart homes.

Sentiment Sensing in contrast benefits from a hype in novel body-worn devices, such as instrumented glasses or biosensors in a number of appliances. Eyetracking is a rich source for the detection of a number of mental activities such as reading or also for the monitoring of attention or, for instance, fatigue. Already today, products are announced which target reading or also for the monitoring of attention or, for instance, to transform the RF-interface into a rich sensing source for environmental activities.

We expect these sensing directions to flourish over the coming years and thereby to advance ubiquitous and pervasive sensing to new borders.

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