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Recent advances in RF-based passive device-free localisation for indoor applications

Sameera Palipana*, Bastien Pietropaoli, Dirk Pesch

Nimbus Centre, Cork Institute of Technology, Bishopstown, Cork, Ireland

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ABSTRACT

Radio frequency (RF) based indoor localisation techniques have gained much attention over the past nearly three decades. Such techniques can be classified as active and passive while passive systems can have either device-assisted or device-free characteristics.

Device-free localisation can be a prominent research field as it transcends other device-based approaches in certain application scenarios. Accordingly, we have witnessed an influx of IDFL research focusing on multiple disciplines including occupancy, positioning, activity and identity. However, despite the recent emergence of several exciting technologies and corresponding techniques, IDFL faces some important challenges and because of this, we haven't come across many mainstream commercial products using RF-based IDFL techniques.

In this article, we survey the recent progress of IDFL prioritising on indoor positioning. We decompose the localisation dimensions into occupants, space and time, provide a detailed taxonomy and a comprehensive review of these techniques. We divide the state of the art mainly into Wireless Network-based and Radar-based, evaluate the respective technologies and the techniques qualitatively, discuss trends, limitations and also indicate future research directions relevant to this field.

1. Introduction

Indoor localisation is a diverse research field having applications in health care [1,2], assisted living [3] and fitness monitoring [4], building automation [5], security [6], retail [7], games and entertainment [8]. It is a much more challenging topic than outdoor localisation due to the requirements of applications (preferably sub-meter level location errors) as well as the challenging nature of indoor environments. Indoor spaces are dominated by multipath, the line of sight may be obstructed in most situations and due to the complex nature of indoor environments, adapting the system to different places is also challenging. Due to these reasons, delivering the accuracies demanded by many applications at a reasonable cost can be a daunting task. Nonetheless, many localisation techniques have been proposed to address these issues and some are slowly finding their way into commercial production [9].

The existing indoor localisation approaches can be classified broadly as *active* and *passive* localisation depending on the participation of the subjects to be localised. Active localisation in particular, relies on subject participation, in essence, dedicated applications in devices or tags attached to subjects communicate with a server to locate or track them. Widely used technologies in active localisation are RFID, infra-red, Ultra-Wideband (UWB), Wi-Fi, GSM, FM, geo-magnetic, Bluetooth, ultrasound or a fusion of data collected from a combination of such methods. As the focus of this survey is on technologies that do not require user participation, a detailed description of active localisation techniques remain out of the scope and we direct interested readers to the following surveys for further details on this topic [10–14].

Comparatively, passive approaches can locate either devices (mobile phones, RFID tags, laptops), humans or other passive objects (objects not having radio capabilities) without their participation. The subjects are usually unaware of a passive localisation system's existence, barring any legal obligations requiring notifications to occupants beforehand. Depending on whether 'a person' or 'a device' is located, these approaches can be further divided into two sub-categories: *device-based* and *device-free*. In *device-based* passive localisation, a device worn by the localisation subject is detected and located by other devices. As an example, a device with Wi-Fi capabilities (e.g. mobile phone) can be tracked by Wi-Fi sniffers [15–17] from the beacons it sends periodically or a simple RFID tag attached to a person can be tracked by a reader [18,19]. In *device-*

* Corresponding author.
E-mail addresses: dhanapala.palipana@mycit.ie, palipana@gmail.com (S. Palipana), bastien.pietropaoli@cit.ie (B. Pietropaoli), dirk.pesch@cit.ie (D. Pesch).

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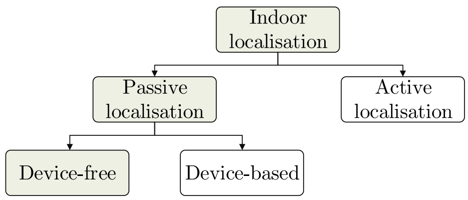


Fig. 1. Classification of indoor localisation schemes. The focus of this survey is highlighted in green. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

free passive localisation, a live (a person or an animal) or a passive object is directly detected and located. Fig. 1 illustrates this classification while Fig. 2a and b exemplify the distinction between active, device-based passive versus device-free passive localisation using two scenarios.

Device-free localisation approaches capitalise explicitly on human body interactions with radio signals in the form of absorption, reflection, scattering and/or diffraction. These approaches transcend other types of active or device-based passive localisation approaches in several applications. In smart homes and smart buildings, detection of occupant presence is one key information for building automation services, assisted living services and the likes. Additionally, accurate occupant locations are important to provide better building automation services [5] and assist in providing higher level context information such as occupants' activities, gestures and identities. Currently, building automation services are often only loosely correlated to occupancy information [20] and can lead to substantial energy wastages in public buildings [21]. Hence, proper exploitation of occupant information has the potential to decrease energy consumption in buildings ranging from 9%-60% [5,22–26] IDFL can also provide assistance to the health sector through localisation and activity recognition in areas such as elderly monitoring [3,4] and fitness tracking [1,2]. Another major beneficiary is the gaming sector [27], which is increasingly moving from game pads to wireless gesture recognition. Intrusion detection [8], law enforcements such as hostage situations, rescue missions [28], and border control [29] are other notable applications. In all the indicated application scenarios occupants or the subjects to be localised are either not committed to carrying a device although they do not oppose being localised, or are reluctant to carry radio devices, or might even be hostile to carrying any device that can localise them which highlights the need of IDFL over active methods [30].

Widely used IDFL technologies in the literature can be classified as being based on radio frequency, optics, sound waves, electrical field or mechanical approaches. We provide a detailed taxonomy of those in Fig. 3 arranged according to the operating frequency. Operating in the highest frequency range, optical methods depend either on visible or infra-red light to locate people. Computer vision-based localisation is heavily discussed because of its affordability, high spatial resolution, and the provision of a large range of information pertaining to size, shape, colour, and texture of the objects. However, this technology has drawbacks due to wall penetration, smoke, darkness [31], and privacy issues [32]. In the past few years, infra-red sensors have made much progress in capturing human motion. These include proprietary systems such as Xbox Kinect [33] and Leap Motion [34] that track a person's movement without wearable devices. Due to the operation in high frequency bands, this technology has two fundamental limitations: low range and requirement of consistent Line-of-Sight (LoS) connection. Sound source localisation faces challenges mainly due to background noise, room reverberation (echoes), and multiple sound sources. Some localisation schemes that use electrical field (e.g. floor tiles) and mechanical devices (e.g. pressure sensors) provide excellent resolutions for occupant locations. Unfortunately, they require heavy investments in infrastructure. For further details on those technologies we direct the reader to the following surveys [35,36].

Radio Frequency (RF)-based IDFL is the primary focus of this survey. RF-based techniques succeed in some key areas where other major IDFL technologies falter: walls, obscurity of vision, privacy, range and compensating the accuracy against cost. The most important signal descriptors used by RF-based schemes are Received Signal Strength (RSS), Channel State Information (CSI), also commonly known as channel frequency response, Time of Flight (ToF) and Angle of Arrival (AoA). Due to the diversity of research in IDFL, we divide the RF-based localisation schemes into two categories as: *Wireless Networks* and *Radar* and provide two separate taxonomies in corresponding sections. These two categories usually associate different signal processing techniques to infer human contexts. As indicated by the name, Wireless Networks fuse data from multiple nodes in the network for localisation. Available Radar techniques on the other hand are mostly variants of Doppler radar and they rely mostly on a single transceiver and the signal processing technique to obtain human contexts.

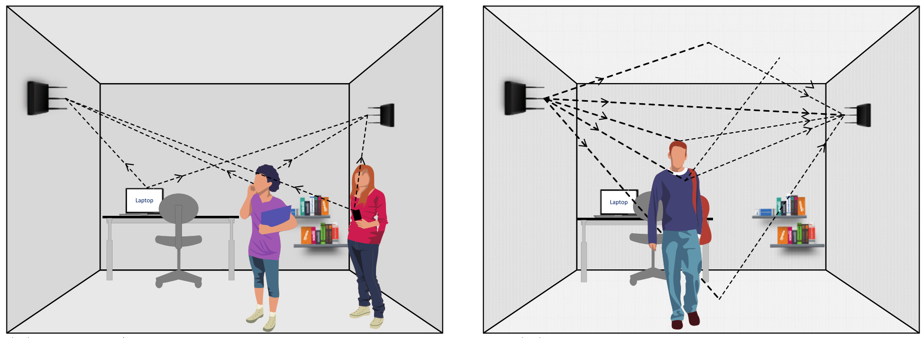
There are several articles that review RF-based indoor localisation. However, most existing surveys review either device-based approaches in-depth [12,13,37] or include both device-based and device-free schemes [10,14,38] together. To the best of our knowledge there is no review that provides an in-depth analysis on device-free localisation specialising on RF technologies. Therefore, in this survey we address this need by providing an in-depth analysis focusing on aspects that are unique to device-free approaches. Thus, the main contributions of this work are threefold:

(i) We divide the localisation dimensions into occupants, space and time and analyse techniques, models and algorithms in the corresponding schemes using these dimensions.
(ii) We compare different technologies based on their strengths, weaknesses and intended applications.
(iii) We also highlight the practical limits of each technology achieved thus far based on important parameters of the corresponding schemes that we consider best. However, currently, there are no benchmarks or standard parameters to judge which schemes are the best. Driven mainly by addressed problems or intended applications, IDFL solutions adopt different technologies, devices and methodologies. Therefore, we use a qualitative approach to compare them.

The remainder of this paper is organised as follows. Firstly, in Section 2 we provide a description of the major signal descriptors adopted by IDFL schemes. In Section 3 we divide the localisation dimensions as occupants, space and time and discuss their granularities. In Sections 4 and 5, we review the literature on IDFL schemes with focus on Wireless Networks and Radar, respectively. In Section 6 we present a detailed comparison of current localisation technologies. In Section 7, we discuss trends, limitations and try to indicate future research directions. Finally, in Section 8 the conclusions are provided.

2. Signal descriptors

Signal descriptors adopted by the majority of localisation schemes include RSS and CSI due to ease of accessibility and usage. Additionally, derived descriptors such as Angle of Arrival (AoA), Time of Flight (ToF), Doppler shift and less prominently, Packet Loss Rate (PLR) and Link Quality Indiator (LQI) also exist. RSS can be advantageous for cost effective applications over AoA or ToF [39,40] as they provide reasonable accuracy even with inexpensive hardware. AoA estimation requires multiple antennas and in fact the resolution is determined by the number of antennas at the



(a) Active/Device-based passive localization

(b) Device-free passive localization

Fig. 2. The distinction between active/device-based passive and device-free passive localisation systems [14]. (a) WiFi access points either measure the received (active) or sniffed (device-based passive) packets to infer the target's position. (b) WiFi devices measure the fluctuation in the signals from nearby devices caused by target obstructions to infer human contexts.

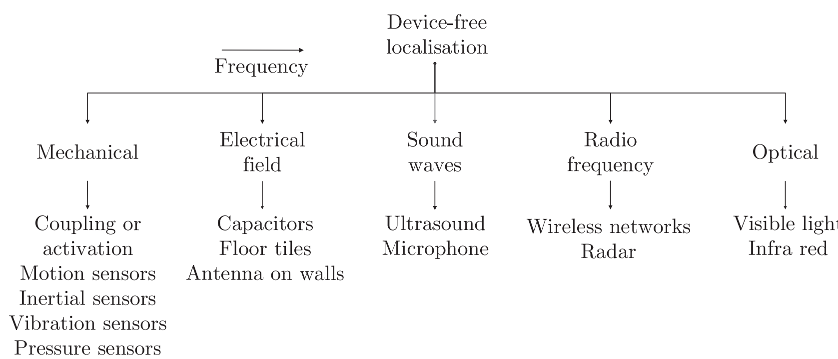
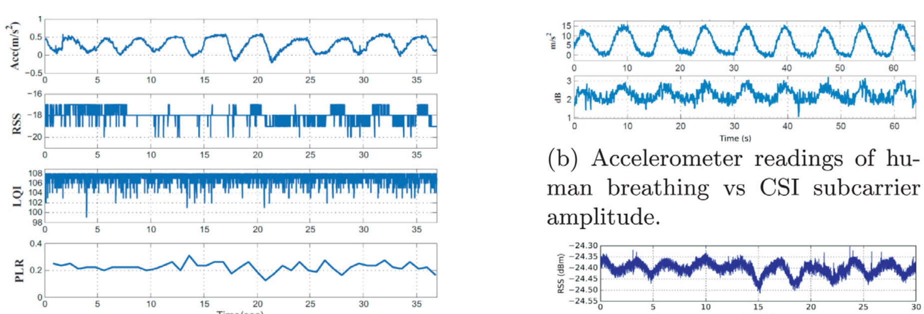


Fig. 3. Device-free taxonomy. The technologies are placed in the increasing order of the operating frequencies. The focus of this survey is highlighted in the green background. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



(a) Accelerometer readings of human breathing compared with RSS, LQI and PLR.

(b) Accelerometer readings of human breathing vs CSI subcarrier amplitude.

(c) Temporal variation of sub-dB RSS

Fig. 4. (a) RSS has the highest temporal correlation with accelerometer readings compared to PLR and LQI, however, the resolution of RSS is limited to 1dB [1] (b) CSI has better correlation with accelerometer readings than RSS and has sub-dB resolution [1] (c) Increase in the resolution of RSS to sub-dB by the method introduced in [43].

receiver [41]. Additionally, AoA estimation requires high computation power for real time performance due to estimation algorithms like MUSIC [42] that depend on Maximum Likelihood estimation. In ToF-based solutions (UWB and FMCW) large bandwidth requirements in the range of 2GHz for precise delay estimations in indoor environments set constraints on hardware costs. Doppler shift occurs only when the reflector is moving relative to the receiver. Doppler shift alone can not locate the target, but can estimate its velocity.

Fig. 4 compares the granularity of different signal descriptors (RSS, CSI, PLR and LQI) obtained through off-the-shelf devices [1]. In the experiment accelerometer readings for human respiration is compared with RSS, CSI, PLR and LQI. As indicated in the figure, RSS fluctuations occur with ± 1dB granularity, thus, minute movements of occupants cause either deviations ≥ 1dB or no change in RSS at all. However, a single subcarrier in CSI provides much higher amplitude resolution in comparison. Consequently, researchers have looked at acquiring sub-dB RSS fluctuations from Commercial Off The Shelf (COTS) devices. Recently Luong et al. [43] demonstrated that using a 100kHz, low power TI CC1200 transceiver and a processor, an RSS estimate of 0.013dB median error can be achieved as shown in Fig. 4c. The advantage of this approach is that they increase the resolution of RSS beyond 1dB granularity using narrowband devices (100kHz) similar to the granularity of WiFi CSI which requires a bandwidth of 10 MHz to 20 MHz. However, this approach needs dedicated hardware like signal processors whereas CSI is easily accessible through commercial devices.

2.1. RSS or CSI?

RSS is still preferred in the majority of applications due to its simplicity in measuring it, however, CSI is gaining popularity especially in presence detection and activity recognition. Wi-Fi devices operating in IEEE 802.11a/g/n standards use Orthogonal Frequency Division Multiplexing (OFDM) as the modulation scheme and send data over multiple sub-carriers in a single channel. The receiver computes fine-grained physical layer information for each Wi-Fi packet such as phase and amplitude of the Channel Frequency Response (CFR) in the form of CSI. In contrast, RSS only provides an average signal strength value for the whole channel. CSI is a good alternative for RSS not only due to high resolution, it also provides detailed characteristics of the wireless link in the frequency domain. In the literature, researchers have extracted different features from CSI to sense humans e.g. amplitude [44] variation of a subcarrier (attenuation in subcarrier amplitudes provide location information), multiple subcarrier ampitudes [45] or phases [46] (as fingerprints), and phase difference of respective subcarriers of two RX antennas [3]. Especially, [3] and [47] report that CSI phase difference of two RX antennas is a sensitive base signal than amplitude. The reason for their claim is that the phase difference of two antennas is a sum of the variations in both antennas. Additionally, phase randomness (which is explained below) that occur using a single antenna can be eliminated through this.

With the IEEE 802.11ac standard's release, CSI-based localisation can get more accurate and robust with Multiple-Input, Multiple-Output (MIMO), beamforming and larger bandwidths. In spite of that, these methods rely heavily on hardware manufacturers' exposure of physical layer channel properties to upper layers via suitable APIs. Currently, CSI is extracted from a limited number of COTS Wi-Fi chipsets (e.g. Intel Wi-Fi Link 5300 [48], Atheros 9k [49]) using modified drivers and firmware. These commodity chipsets exhibit some problems that curtails CSI's full potential:

(1) Due to low bandwidth (20MHz and 40MHz of IEEE 802.11n) and multipath propagation, the channel frequency response from CSI constructs only a coarse-grained Channel Impulse Response (CIR) [50], unlike in ultra-wideband.
(2) Random packet detection delay, sampling frequency offset (phase rotation), residual carrier frequency offset inherent in these chipsets cause random phase variations over successive received packets [51].

There are solutions for lower bandwidth such as switching through multiple channels within the channel coherence time of the indoor environment [52,53]. However, this may introduce additional issues with regards to interference to other WiFi devices. Phase randomness can be eliminated to some extent in the form of a linear transformation (true phase cannot be recovered from this approach) [51,54]. Nonetheless, recent studies have shown that there are non-negligible non-linear phase errors (due to IQ imbalance issues in direct down conversion) which cannot be eliminated through this approach [55].

Considering these limitations of COTS hardware/WiFi chipsets, Software Defined Radio (SDR) implementations of the Wi-Fi physical layer can be a much better option for CSI-based device-free localisation schemes e.g. [56]. SDRs can eliminate the above shortcomings at a slight expense in complexity and cost. Furthermore, they can enhance the capacity and coverage with antenna arrays having MIMO capabilities, high bandwidths (in the range of 1GHz) and fast signal processing. The ultimate goal of SDR studies is to identify a path towards a compact & cost effective system-on-chip solution.

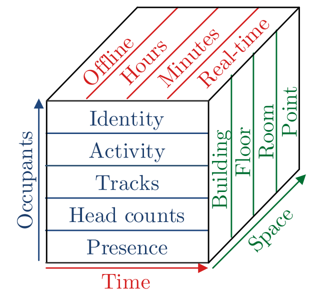


Fig. 5. Localisation resolutions in multiple dimensions proposed in this work. This is a refinement of the occupancy resolutions by Melfi et al. [57].

3. Localisation dimensions

There is a clear affiliation between IDFL and occupancy detection. For the proper functioning of an IDFL scheme, detection of human presence prior to positioning is an essential requirement. Besides, we can argue that IDFL is just fine grained occupancy data. Due to this relationship, we retain the decomposition of occupancy dimensions proposed by Melfi et al. [57]: granularity of 'time', 'space', and 'occupants' in this survey, but refine them to propose the decomposition shown in Fig. 5 for IDFL schemes. The time and space dimensions are quite trivial; if a system is capable of providing the occupancy information of precise positions in 'space' in real-time (also called real-time indoor positioning), then it is also capable of providing the occupancy of rooms, floors or buildings either in real-time or with a reduced time granularity depending on the system's capabilities. In this context, the 'occupants' dimension becomes significant, and it can be decomposed as follows:

(1) Presence (Is this space occupied?): Information whether a space is occupied or not is the most primitive form of intelligence provided by IDFL.
(2) Head counts (How many are there?): Obtaining the number of people present in a room or a zone can be complicated as RF-based systems sense humans through signal fluctuations, and the fluctuations caused by multiple occupants may depend on their motion. Therefore, we see that many systems focus on obtaining head counts in rooms based on specific human motion models [58,59]. Occupant presence is a precursor to head counts.
(3) Tracks (Where were they before?): This refers to the trace of where people were before their current position. Therefore, presence and head counts are precursors to tracking. However, as described by Teixeira et al. [35], tracking can be ambiguous. For instance, the track of people leaving the system (e.g. leaving the building) then re-entering the system (e.g. entering the building again, for instance the next day) would not have a track over multiple days if identified only with a temporary and anonymous ID.
(4) Activity (What are they doing?): The type of activities that current systems recognise range from full body activities like walking, jumping, falling, sitting, sleeping etc. as well as activities involving parts of the body such as hand gestures, head movements, mouth gestures etc. One can also argue that location is a property of the activity, however, in this survey we have a specific dimension for location as 'space'.
(5) Identity (Who are they?): Some systems are able to provide unique identities for people. This is the case, for instance where a locating system uses RFID in active/device-

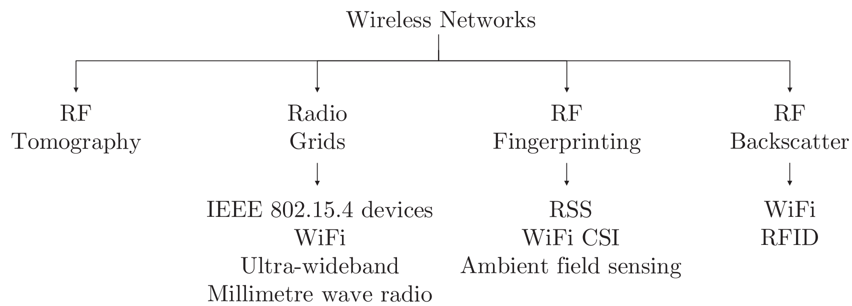


Fig. 6. Wireless networks taxonomy.

based approaches. Identity enables non-ambiguous tracking as people are differentiated by attributing a permanent ID.

However, constrained by its potential, not every technology may provide human contexts in granularities in the above order in practice. As an example, technologies like IEEE 802.15.4 devices (e.g. TelosB, MICAz motes) or RFID may only address a specific problem like inferring the position of a person assuming the human presence as a given.

With this decomposition of dimensions subsumed under the term localisation, in the following sections, we analyse schemes that have had a significant contribution in IDFL. Therefore, we use the term 'localisation' generally to encompass all the above dimensions even though we prioritise indoor positioning schemes in this survey. However, below we also mention presence detection, counting, tracking or activity recognition solutions that have models or techniques that can be adaptable to enhance indoor positioning. Unless otherwise noted, the localisation targets of the mentioned schemes are humans.

4. Wireless networks

Device-free localisation in *Wireless Networks* is typically referred to in the literature as *RF sensor networks* [60] or *sensorless sensing* [61]. In the following sections, Wireless Networks are further divided and discussed in terms of *RF Tomography, Radio Grids, RF Fingerprinting* and *RF Backscatter* depending on the technique used for localisation. Then they are divided into subcategories depending on the types of technologies that use the corresponding technique. Fig. 6 illustrates this classification.

4.1. RF tomography

This technique estimates changes in the propagation field based on the mean attenuation or the shadowing in radio links caused by objects. To compute the attenuation during localisation, an off-line training phase that is free from humans is a prerequisite. Subsequently, a linearised shadowing model constructs an image of this field or directly provides the object coordinates using particle filters. The transceivers are arranged as shown in Fig. 7a to surround the target to construct its attenuation two dimensionally. Applications for *RF Tomography* mainly lie in areas such as intrusion detection [29,62], elderly monitoring [31,63] or rescue operations [28].

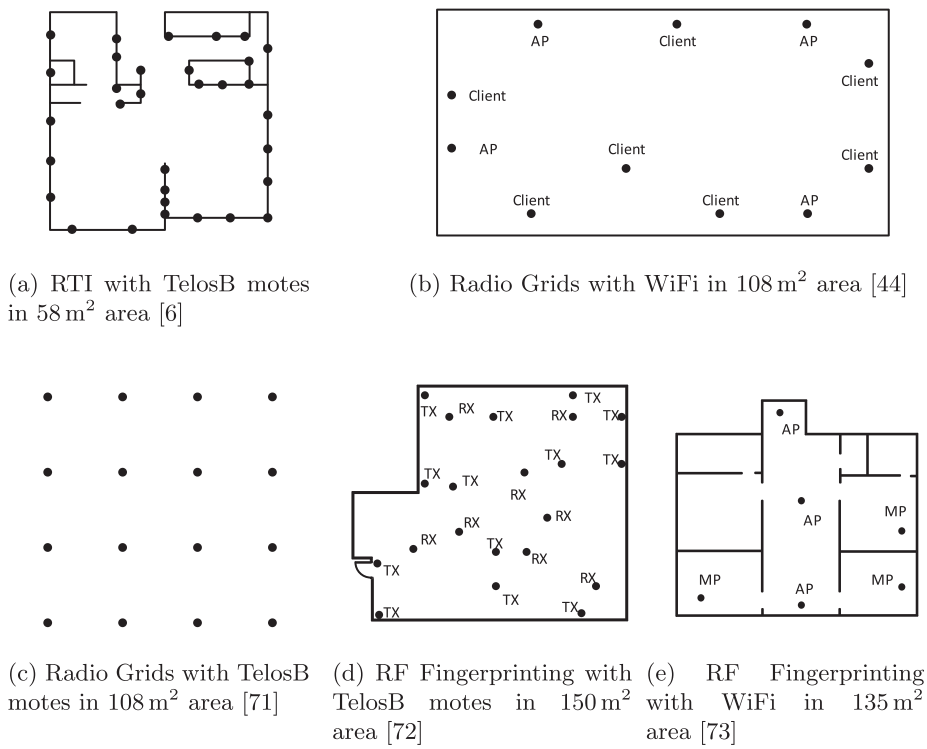
In the literature, the term Radio Tomographic Imaging (RTI) is used for these approaches, essentially, when an image of the located object is constructed. If so, a Kalman filter must track the image which is an additional requirement that may induce more noise into the position estimation. Wilson and Patwari's findings [64] that commercial IEEE 802.15.4 transceivers achieve tomographic imaging similar to Computed Tomography (CT) in medical applications, provided a breakthrough for research in this area. RTI requires a large number of radio transceivers around the target area to obtain a satisfactory resolution. For example, in the work by Kaltiokallio et al. [6], cited by Bocca et al. [65] as the most accurate model, 30 nodes were deployed around an area of $70m^2$ obtaining a mean positioning error of $\approx$ 30 cm for a single person. This method utilises the frequency diversity in radio links and the idea that the spatial impact area of humans varies for each link. Furthermore, they achieve the given positioning error also in challenging environments such as through-wall and cluttered indoor.

To locate multiple targets in a cluttered indoor area, particle filter-based tomography approaches have been successful [66,67]. Although particle filters provide good accuracy for multiple persons, real-time result acquisition is constrained by processing requirements. Variance-based Radio Tomographic Imaging (VRTI) uses temporal RSS variation quantified as variance to track moving persons. Wilson and Patwari introduced this method by tracking a person with $\approx$ 45 cm mean error in a 34 node set-up [62]. This approach has applications mainly in intrusion detection and tracking mobile persons [62]. However, it has issues in locating stationary persons. In such cases, signal variation slowly decreases, causing the object to gradually disappear from the constructed image. This method does not require off-line training and performs better than shadowing-based *RF Tomography* in non-LoS conditions. Apart from the mean and variance of RSS, kernel distance [68] is another commonly used metric in IDFL [69]. Quantifying the changes in mean, variance and other qualities of the RSS distribution in one metric, it mitigates the shortcomings of stand alone metrics like mean and variance and thus, performs better at locating stationary or moving persons in LoS and non-LoS conditions [70].

In essence, *RF Tomography* shows promise in positioning and tracking of multiple persons (up to 4), in both LoS and non-LoS. It also achieves a low error in the sub-meter range using COTS devices. However, it may be impractical for some applications due to the requirement of high sensor densities in small areas. Furthermore, as the tracked object needs to be surrounded by the transceivers at a height of $\approx$ 1 m above the ground to obtain the object's attenuation image, this sets constraints on transceiver placement.

4.2. Radio Grids

The distinguishing feature about *Radio Grids* from other approaches is that they utilise models to characterise signal strength fluctuations in multiple links to detect an object's presence or position in the target area. Transceivers are merely arranged in grids to extend the target area. These methods largely rely upon a training phase to calibrate the model parameters such as node positions and signal strengths of the links for the unoccupied environment and an online phase to perform the actual localisation. Below we analyse these approaches categorised based on the associated technologies: IEEE 802.15.4 compliant devices, WiFi, RFID and ultra-wideband.



(a) RTI with TelosB motes in 58 m^2 area [6]

(b) Radio Grids with WiFi in 108 m^2 area [44]

(c) Radio Grids with TelosB motes in 108 m^2 area [71]

(d) RF Fingerprinting with TelosB motes in 150 m^2 area [72]

(e) RF Fingerprinting with WiFi in 135 m^2 area [73]

Fig. 7. Placement of transceivers in RTI, Radio grids and RF Fingerprinting. RTI and Radio Grids using TelosB motes have restrictions on transceiver placement. WiFi can afford less transceivers than TelosB motes.

4.2.1. IEEE 802.15.4 compliant devices

In these approaches, low power TelosB motes are generally deployed. Due to the low transmit powers (<1dBm) and low bandwidth (2 MHz), these techniques usually associate with large grids to achieve reliability and long range. The seminal work on this was done by Zhang et al. [74]. They deployed a radio grid on the ceiling as depicted in Fig. 7c and observed that links which are most influenced by a person tend to be closely grouped. Furthermore, they reported that the highest fluctuations in RSS due to a person's movement occur along the link line and a line perpendicular to the link around its midpoint. Based on the observations, they developed a model for signal dynamics and located a person with three different algorithms: *midpoint, intersection* and *best cover*, whereby centre points, intersection points or rectangular areas of the influenced links were computed to estimate the object position in the corresponding algorithm. In a 108m^2 empty room with a 4$\times$ 4 sensor grid placed on the ceiling, they report average errors of $\approx$ 0.7 m for a single person and $\approx$ 1.8 m for two persons.

To locate two persons at least 5 m apart, these algorithms were further improved by dynamically clustering the influenced nodes with an error of $\approx$ 1 m [71]. By allocating different frequencies to different node clusters minimizing interference among neighbouring nodes, a lower error and a lower latency was achieved albeit a relatively higher node density (23 TelosB motes in a 64m^2 area) [75]. In this method, two mobile persons who are at least 2 m apart were tracked and the experiments were conducted in a non-cluttered environment. However, the performance of this approach in a realistic indoor environment with furniture, computers, and metallic objects which will greatly impact the multi-path effects or, increasing number of people, moving objects which will interfere with the characterisation of the empty space remains largely unexplored.

Table 1
Different applications of CSI-based human sensing. The applications are divided as primary and secondary because outputs of secondary applications are inferred from outputs of at least one primary application.

	Application	Reference
Primary	Presence detection	[45,80–83]
	Respiration monitoring	[76–79]
	People counting	[58]
	Walking Speed estimation	[84,85]
	Walking direction estimation	[86]
	Imaging of humans and objects	[87]
Secondary	Location	[44,45,88]
	Activity recognition	[7,89–91]
	Fall detection	[3]
	Smoking detection	[92]
	Sleep monitoring	[1,93]
	Gesture recognition	[94–97]
	User Identification	[98,99]

4.2.2. Wi-Fi

Unlike TelosB motes, Wi-Fi offers both RSS and CSI signal descriptors. Initial WiFi based approaches adopted RSS fingerprinting for localisation. However, recent Wi-Fi IDFL solutions with model-based approaches have involved CSI instead of RSS mainly. Therefore, in this section we discuss CSI-based COTS and SDR solutions and discuss WiFi RSS-based approaches in Section 4.3.

Sen et al. [54] introduced the usage of CSI in COTS Wi-Fi devices and demonstrated that aggregation of channel frequency response across several OFDM sub-carriers provides location fingerprints. Since then, due to the versatility and finer granularity of CSI, a profusion of IDFL applications have materialised, Table 1 provides a summary of them. Initially, the applications were just limited to motion detection, location inference and activity recognition, however, recently the research has branched out to many

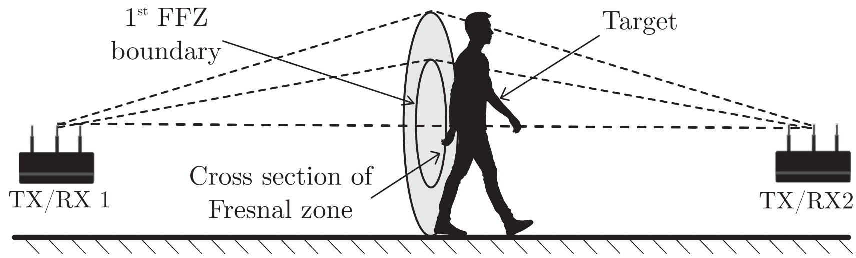


Fig. 8. The use of Fresnal zones to model the LoS effects in [44].

other areas as indicated in the table. Currently, stationary person detection using CSI is a trending topic due to CSI's high resolution. People have looked into this problem either as breathing detection [76–79] or efficient extraction of features to effectively isolate unoccupied environment from the occupied [80].

The absence of an analytical model to map the impact of humans on CSI obtained through commodity chip-sets has been a long standing issue. The reason is partly due to the randomness in phase. Depatla et al. [59] use a statistical model on RSS to estimate the number of people in a target area. They also claim that the model has potential to model CSI amplitudes. They separate the effect of a person on the WiFi signal into: blocking the LoS as well as nLoS scattering, therefore, the received signal, h can be expressed as follows:

$$h = a_0 e^{j\phi_0} + \sum_{i=1}^{N} b_i e^{j\psi_i} \tag{1}$$

where a_0 and ϕ_0 represent the resultant amplitude and phase of the combined effects of LoS component (taking into consideration the blocking of LoS by humans) and multipath components due to static objects, and b_i and ψ_i indicate the multipath components due to walking people. They characterise a_0 probabilistically by developing a human motion model, the distribution of b_i is represented by K-distribution (widely used to model sea clutter when the scatterers are low) and all the phases are assumed to be uniformly distributed (due to operation in a high frequency). Accordingly, they obtain the probability distribution function (PDF) of h and use Kullback Leibler divergence to measure the distance between the PDF of h and the distribution of measured received signal to predict the total number of people. They estimate up to 9 people in a 33m^2 area and the error is 2 or less 63% of time.

More recently, CARM [91] characterised human speeds on CSI subcarrier amplitudes and extended this to an activity model. Thereby, CARM built an *environment independent* activity recognition scheme and achieved more than 80% accuracy in classifying eight activities. Since then, a variety of models characterising CSI amplitude due to human presence have emerged [44,79,80]. However, the basis of all these models is to model subcarrier amplitude by isolating static paths due to scattering and reflection off stationary objects from dynamic paths caused by human intervention. Among these models, LiFS [44] stands out due to the fact that it models subcarrier amplitude variation when the link experiences LoS shadowing by a human, whereas, other models handled only the fading caused by nLoS movement. LiFS addresses this by dividing the space surrounding the link into three zones: LoS, nLoS First Freznel Zone (FFZ) and outside of FFZ as shown in Fig. 8. Characterisation of CSI amplitude, H in LiFS is as follows:

$$H = \begin{cases} L + D_t + A_t & \text{if LoS} & (2) \\ L + D_t + \eta & \text{if nLoS and in FFZ} & (3) \\ L + \eta & \text{if outside of FFZ} & (4) \end{cases}$$

where L is propagation loss, D_t is diffraction fading, A_t is target absorption attenuation and η is measurement noise. Using this model, LiFS obtains an effective value for CSI amplitudes which depends on object positions by filtering out subcarriers that do not conform with the model. This approach is able to locate a human without offline training with .5 m median error in LoS and 1.1m nLoS.

In addition to deriving the distance of a target using the attenuation of CSI subcarriers, AoA information can also be used. Due to different ToFs of different signal paths, incoming signals encounter varied phases in different antennas as well as among subcarriers of the same antenna. MaTrack [100] exploits this fact to derive the AoA information using a modified MUltiple Signal Classification (MUSIC) [42] (MUSIC algorithm is widely used to estimate the AoA from received signals using multiple antennas) algorithm on each receiver and thereby, uses triangulation to locate a human. As MaTrack leverages the incoherency of the reflected path from human compared to the direct path, it does not require offline training to locate the human and achieves .6 m median location error in a $\approx$ 70m^2 uncluttered area. However, when the person is static, it experiences lower detection rates due to low incoherency of reflected paths.

Compared to COTS chipsets-based solutions, SDRs offer the ability of CSI amplitude and phase to be incorporated in fine-grained AoA and ToF measurements. Using SDRs, Doppler shift of a signal caused by human movements can be easily extracted. Doppler shift caused by human movements is only a few Hertz, whereas, the frequency offset between a transceiver and a receiver of a commodity WiFi chipset is few hundred Hertz causing the Doppler shift to be hidden in phase randomness. Additionally, packet detection has to be conducted in nanosecond rates which is impossible with commodity chipsets. SDRs mitigate these issues by precise TX-RX synchronisation and high speed signal processing using FPGAs. Pu et al. [56] developed a prototype using USRP-N210 software radios for gesture recognition in indoor environments. They were able to classify nine gestures with a 94% accuracy by capturing Doppler shifts having a resolution of a few Hertz. [101] used a device-free human motion detection method using Doppler shift and located the position by measuring the AoA using directional antennas.

However, it must be highlighted that CSI-based IDFL is still evolving compared to its active localisation (targets carry devices that cooperate with infrastructure to localise) counterpart. Examples of advanced active localisation systems include ArrayTrack [102], which locates 41 users in an office environment to within a 23 cm median error, CUPID [103], which locates an object using just one access point with 5m median error and iLocScan [104], which simultaneously locates a target and maps the area as it moves. All these methods used SDRs as the main hardware for localisation. More recently SpotFi [52] achieved an accuracy of 40 cm using only commodity WiFi devices, a performance comparable to that of ArrayTrack.

4.3. RF fingerprinting

In fingerprinting, a radio map must be initially constructed off-line by placing a person at predetermined positions in the area of interest. During the on-line phase, collected RSS values are compared with the fingerprint, and the corresponding position is inferred. Applications of this approach are mainly elderly health care, home security and energy management in buildings [72].

4.3.1. RSS

Among RSS based approaches, Youssef et al. [105] introduced the first fingerprinting IDFL scheme using COTS Wi-Fi transceivers. They detected a mobile person with moving RSS average and moving RSS variance, and tracked them using a Bayesian inversion based inference approach. This approach was further enhanced by Kosba et al. [106] to track a person in a real indoor setting. They also compared different Access Point (AP) configurations to enhance the overall performance. Nuzzer [73] leveraged single person tracking into multi-person tracking by dividing a large area into multiple zones either as actual rooms or small areas separated by radio links. It located a person with less than 2m positioning error in a real environment using five 802.11b Wi-Fi devices in a 130m^2 area. SCPL [72] used a successive cancellation method to detect and locate multiple persons where the impact of the first detected object is subtracted from the overall RSS. It detected four people in an office cubicle area (150 m^2) and an open floor area (400m^2) using 20–22 Chipcon CC1100 radio transceivers with a mean positioning error of 1.3m for both areas.

More recently, ACE [107] tried to address the exponential growth of localisation complexity with increasing number of people in fingerprinting. They used a cross-calibration approach to minimise the calibration overhead of multiple entities to a linear complexity. They recorded median location errors of 1.33m and 1.43m for a single person, 2.11m and 1.44m for three persons in 140m^2 and 130m^2 areas, respectively.

4.3.2. CSI

The goal of initial CSI based fingerprinting approaches was to distinguish human motion from the unoccupied environment. A common intuition among these methods is that the affected multi-paths due to human motion would reduce the similarity between CSI measurements of unoccupied and occupied environments. Therefore, a distance measure between a fingerprint of an unoccupied room CSI batch and CSI measurements obtained during human motion is used as an indicator of human presence. As the structure of CSI is high dimensional compared to RSS, various distance measures have been proposed. Pilot [45] used cross correlation as the distance measure, [108] extended it to an adaptive method that automatically adjusts the threshold depending on the environment. Xiao et al. [109] used grey relational analysis to measure the distance. Omni-PHD [82,110] used a statistical approach and its fingerprint is a histogram of CSI amplitudes. They used Earth Mover's distance [111] to measure the distance between unoccupied and occupied histograms. Even though they all tend to have detection rates in the range of 90% in unique environments, a systematic comparison of their capabilities are non-existent. Pilot [45] in particular, is a prominent fingerprinting approach that uses CSI for locating people as well. It uses CSI amplitude to generate fingerprints. Once an occupant is detected, it uses kernel density based maximum a priori estimation algorithm to estimate the occupant position taking raw CSI values as fingerprints. Compared to RSS-based fingerprinting approaches like Nuzzer [73] which was mentioned above, Pilot can achieve upto 10% increase in accuracy for locating a single person.

4.3.3. Ambient field sensing

Ambient field sensing systems do not have dedicated transmitters. Instead, they sense the ambient field or the already available signal in a wide range of frequencies (e.g. FM band) using SDRs or other dedicated receivers. They typically infer the object presence and the position with fingerprinting methods. Therefore, we include ambient field sensing methods as a sub category of fingerprinting approaches.

An initial feasibility study of an ambient FM sensing scheme in a domestic environment was conducted by Popleteev [112]. By sniffing 200kHz channels in the 87MHz–111MHz band using SDRs, the study identified a correspondence between distinct subject positions and unique signal strength patterns in the FM spectrum. Based on this observation, the position of an individual was obtained using a k-Nearest Neighbour (kNN) classification. Later, Popleteev and Engel [113] enhanced this to a fine-grained localisation scheme. They achieved a sub-meter level upper bound for 90% errors locating one person in a 18 m^2 room. However, they observed an increase in the error over time, particularly, within five days the error increased by $\approx$ 1m. Shi and Sigg [114] demonstrated the feasibility of simultaneous human localisation and activity classification using ambient field sensing. They used two SDRs, separated by 4m, for a rather small, 2m^2 area. They distinguished three activities at two different positions using Naive Bayes, kNN and decision tree based methods, and report an activity classification accuracy of more than 70%. Later, they enhanced this to recognise five activities including empty, walking, lying, crawling or standing [115]. However, they report that best classification accuracies occur when the activity is conducted within .5m–1m from the receiver.

4.4. RF backscatter

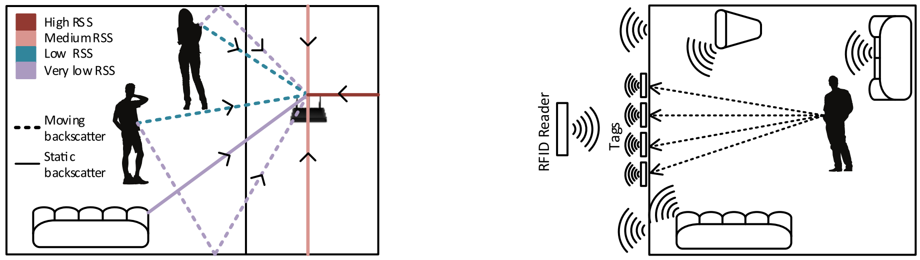
Backscattering, the reflection of signals back to where they originated has similarities to the flashing effect in photography or weather radars. It has recently been deployed for IDFL as well in which the wireless transmitter acts as the light source.

4.4.1. Wi-Fi-based

WiDeo [116] extended backscatter measuring to Wi-Fi devices. In WiDeo, wireless transmissions of the Wi-Fi AP is the equivalent of light source and the reflection of this back at the AP (backscatter sensor) is equivalent to the motion tracing camera. Fig. 9a illustrates this. The backscatter sensor distinguishes objects using three features of the reflected RF signal: amplitude, ToF and AoA. The authors built a prototype based on this principle. WiDeo consists of SDRs [118] mimicking the functionality of Wi-Fi APs having a bandwidth of 20MHz at 2.4GHz. Each AP is attached to four antennas enabling MIMO capabilities which helps with ToF and AoA computations. The authors mention that this system can trace up to five motions concurrently with a mean error of 12 cm. The impressive fact in this work is the low error achieved in a relatively lower bandwidth scenario compared to other fine-grained motion tracking schemes.

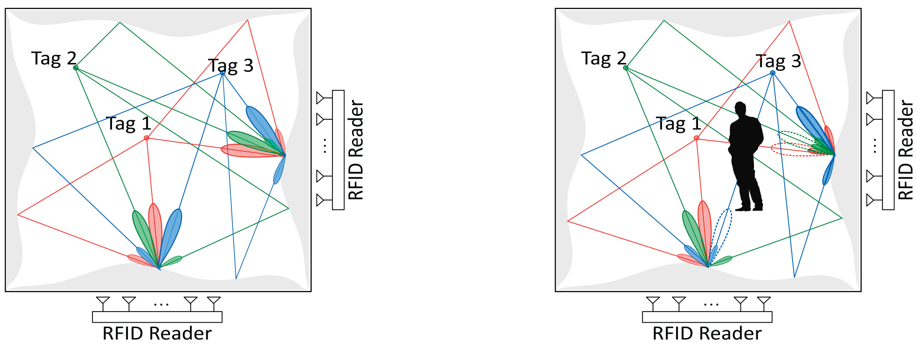
4.4.2. RFID-based

Unlike in *active* RFID localisation, device-free schemes attach RFID tags to static objects of the target area. When an RFID tag receives a signal from a reader scattered by a moving object, it reflects a modulated RF signal indicating either occupant presence or absence which can be considered as a backscatter signal. Here, the human presence influences both the forward and backward waves. Fig. 9 compares this to WiFi backscatter localisation. The communication range of RFID technology has currently increased up to orders of 10m. It is also reported that major manufacturers are trying to increase this range further [119] by increasing the sensitivity



(a) WiFi backscatter (b) RFID backscatter

Fig. 9. (a) Wi-Fi AP acting as a light source and a backscatter sensor for through-wall motion detection in WiDeo [116] (b) When an RFID tag receives a signal from a reader scattered by a moving object, it reflects a modulated RF signal indicating either occupant presence or absence [117].



(a) No person (b) 3 paths blocked by a person

Fig. 10. RFID readers infer the direction of the person through the power decrease in the paths of respective directions [119].

of the RFID readers and high transmit powers (≈ 30dBm) which might further encourage RFID-based IDFL efforts.

TagTrack [120] leveraged this idea to measure the RSS fluctuations caused by humans. It located and tracked a person by Hidden Markov Model (HMM)-based statistical methods and achieved a 7 m mean tracking error and a tracking accuracy of 98% in a 3.2 × 4.8 m area.

Tadar [117] used RF-backscatter for through-wall localisation of moving humans. In this scheme, the reader is the equivalent of the light source while the RFID tags form a virtual antenna array and function as the backscatter sensor. Fig. 9b shows this behaviour in a through-wall scenario. The RFID tags were deployed on the same side as the reader. The authors required a high-gain directional antenna to recover the weak through-wall reflections. The flash effect (strong reflection off the wall, 5 inch hollow wall and an 8 inch concrete wall) was removed by subtracting the learned signals of the empty room by assuming a linear channel. They modelled object motions using an HMM, whereby the object trajectory was obtained through the Viterbi algorithm and report impressive median tracking errors of 7.8 cm and 20 cm in X and Y dimensions. They required 45 RFID tags and a reader for a 7×4 m area. The tags were placed inside a 61× 43× 33 cm box with a 5 cm separation and they basically function as an antenna array. This way the deployment overhead can be reduced as well.

D-Watch [119] used the backscatter technique to obtain AoA information to locate an object using commodity tags and readers. This technique requires at least two readers and multiple tags (<50) to successfully locate an object. D-Watch RFID readers identify the angle of the human from the power drop at the respective direction due to shadowing of the path between the reader and the tag, whereby, triangulation infers the human position. Fig. 10a and b illustrate this. To identify the power drop in a particular angle, D-watch uses a modified version of the MUSIC algorithm. One key difference of this approach is that it does not require the positions of the tags in advance to locate a person which reduces deployment overheads. However, to rectify the random phase offsets introduced by the commodity tags, D-Watch requires deployment of some tags with known direct path angles. In rich multipath environments ($70m^2$) it can track a human with 16.5 cm median error.

4.4.3. Ultra-wideband (UWB)

UWB transceivers have the luxury of a much larger bandwidth than many other technologies. Consequently, they obtain a more precise channel impulse response which is helpful in narrowing down the target's range. Hence, UWB ToF-based localisation is more popular than inaccurate RSS measurements or AoA-based methods that require large antenna arrays. However, UWB transceivers are more suitable for short range applications as they send low-energy impulses.

In early work, detection of human presence by ultra-wideband radios was implemented through breathing detection. Yarovoy et al. [121] demonstrated in a laboratory setting that human detection through breathing/motion can be accomplished using UWB in the 1GHz–12GHz band. Chang et al. [122] detected human presence in a dynamic outdoor environment, then extended this to a ranging and tracking system of up to two people [123] and then provided insights on how to distinguish humans from other moving objects [124].

More recently, Kilic et al. [125] produced preliminary work on a device-free person detection and ranging method that avoids the need for calibration. It utilises low-frequency signal variations induced by human presence which is more conspicuous than background noise. Using a likelihood ratio between the received signal power and the signal power without the human reflection component, they have captured a test statistic. An occupant is detected if the test statistic exceeds a predetermined threshold. This was later developed to locate an object position with an error in the range of 12 cm–180 cm using four UWB radios in a $15m^2$ area [126]. Since the radio nodes are hung from the ceiling, this approach is scalable to large spaces.

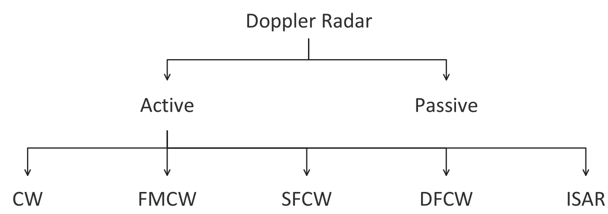


Fig. 11. Radar taxonomy.

4.4.4. Millimeter wave radios

Wireless signals cannot easily penetrate objects that are larger than their wavelengths, thus, reducing the wavelength induces more reflections. This principal can be leveraged to locate smaller objects like pens in very short ranges ($\approx$ 1 m) which can not easily be located by conventional technologies that use either 2.4 GHz or 5 GHz industrial, scientific and medical (ISM) bands.

mTrack [127] uses 60 GHz radios that are standardized as IEEE 802.11ad for this purpose. 802.11ad standard permits the use of multiple antenna elements to produce highly directional beams that can be steered electronically. Lower wavelengths and highly directional antennas produce high sensitivity to small changes in object position. mTrack uses both RSS and phase (relative to transmitter) to locate and track an object. It is implemented on SDRs and requires one 60 GHz transmitter and two receivers. When an object moves in the target area, the path length of the reflected signal varies altering the signal's phase. By measuring the direction of reflected signals, each receiver estimates the object's relative angle, thereby, locating the object. Due to short wavelengths and steerable antennas, mTrack can achieve location errors upto 8 mm, however, its range is limited to just 1m due to high operational frequencies. Therefore, mTrack can locate only miniature devices like pens. The authors report that this technology has applications in areas such as wireless transcription and virtual trackpad (virtual user interface).

5. Radar

There has been major interest recently in the research communities to leverage radar techniques for IDFL. The main driver is the involvement of SDRs in radar localisation, replacing dedicated or proprietary hardware. We divide the existing radar localisation solutions as active and passive radars.

Active radars are the traditional radars where a radio signal is emitted from a transmitter and reflects back towards the emitter location. We divide active radars further into *Continuous-Wave (CW), Dual-Frequency CW (DFCW), Frequency-Modulated CW (FMCW), Stepped-Frequency CW (SFCW)*, and *Inverse Synthetic Aperture Radar (ISAR)*.

A passive radar system relies on the illumination of the target from a signal emitted by a non-cooperative/non-radar transmitter to detect and localize the target. These systems exploit a range of transmission sources including Global System for Mobile (GSM) [128–130], Long Term Evolution (LTE) [131,132], Digital Video Broadcasting (DVB) [132,133], Frequency Modulated (FM) [134] and WiFi [135–139]. Fig. 11 illustrates the radar taxonomy depicted in the survey.

5.1. Active radar solutions

CW radar is the traditional Doppler radar and it is also known as *Interferometry Radar*. The transmitter and receiver in these systems are physically separated because they have to function concurrently, however, they are almost collocated, typically assembled in a single system. It measures the Doppler shift of reflected signals, whereby objects with regular motion or moving parts that cause micro-Doppler motions are detected [140]. *CW Radars* experience range ambiguities due to range dependence on signal phase which is modulo 2π, hence, these radars are primarily used for human presence detection using vital signs such as heartbeats [141]. Dual offbeat carrier frequencies of *DFCW Radars* eliminates the range ambiguity in *CW Radar*. Amin et al. [142] demonstrated its capabilities of detection and range estimation of targets for carrier frequencies 906.36 MHz and 919.82 MHz in an anechoic chamber and a through-wall setting.

FMCW which is another variant of *CW radar* estimates object positions by mixing a transmitted frequency chirp with the reflected wave to produce a beat signal. The instantaneous frequency difference between the two waves is proportional to the object range. This is a widely researched area among Doppler radar techniques. Consequently, it has made much progress in areas related to smart homes such as presence detection from vital signs (heart beat and breathing) [4,143] multi-target localisation [8], gesture recognition and human identification [144]. Other major applications of FMCW research include automotive radar systems [145–147] range and velocity detection [148], imaging of humans [144], indoor positioning for gesture recognition [27], and intrusion detection and rescue operations [8].

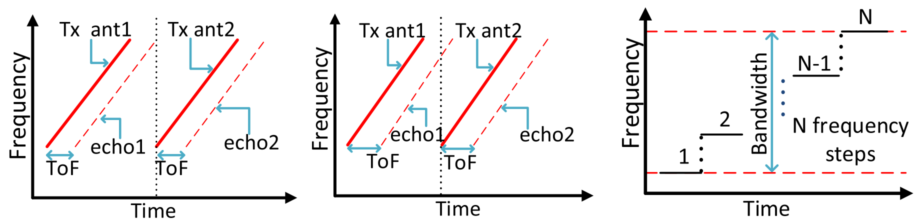
A common limitation among most RF-based localisation systems is the identification of users through walls and occlusion. Using an SDR-based *FMCW Radar*, WiTrack [27] attempted to solve this, and managed to locate a human in three dimensional space with a mean error in the range of two decimetres. Particularly, WiTrack is capable of through-wall localisation, fall detection, and gesture recognition of a single person. The radar consisted of a custom made RF front-end with three receiver antennas and one transmitter antenna. In WiTrack2.0 [8], this was extended to locate up to five stationary or mobile persons simultaneously, and a 11.7 cm median error was achieved. As the number of transmitter-receiver antenna pairs were dependant on the number of users, multipath effect and noise in the environment, WiTrack2.0 required five antenna pairs to locate five users, although multipath effect and interference among multiple antennas were two major issues. To counter this, multi-shift FMCW was introduced in which each antenna transmits with a specific delay (maximum ToF in the target environment) to the preceding antenna. Fig. 12a and b illustrate the difference between FMCW and Multi-shift FMCW operation.

Wang et al. [149] tackled the problem of simultaneous localisation of stationary and moving objects by developing a hybrid FMCW-CW radar technique. This radar system is able to continuously alternate between the FMCW mode and the interferometry mode as both modes of operation can share the same RF front-end. Consequently, this system is capable of both life activity monitoring and localisation, and creates a 360° view of the indoor environment. The authors report a maximum error of 10 cm in a $\approx$ 60 m^2 area.

Similar to *FMCW Radar, SFCW Radar* provides both range and speed characteristics of a mobile target. As indicated in Fig. 12c, it retains a stepwise increase in frequency over time. Object detection and speed estimation is performed using the Doppler shift as in *CW Radar* while range is estimated based on the time difference of transmitted and received signals. However, this radar is rarely used in indoor localisation and generally, applications have focused on fall detection [150] and health monitoring [151].

5.2. Passive radar solutions

As passive radar systems rely on the already deployed technologies for sources of illumination, they are low cost solutions for ex-



(a) FMCW (b) Multi-shift FMCW (c) SFCW

Fig. 12. (a) Antenna 2 in FMCW transmits when the full echo of antenna 1 is received, (b) Antenna 2 in Multi-shift FMCW may transmit before the full echo of antenna 1 is received depending on the ToF of the room (c) Stepwise transmissions in an SFCW radar.

isting active radar techniques. As the transmitter of opportunity and the radar receiver are physically separated, these radars have either bistatic or multistatic structures. Among existing works, passive radar systems exploiting WiFi signals are popular for indoor localisation because WiFi is ubiquitous in indoors and has reasonable bandwidth for range resolution [152]. As these systems rely on external sources of illumination such as WiFi, they are linked to both wireless networks and radars.

Recent passive radar deployments have focused on SDR architectures which provide a more flexible software based approach for radio design. They provide several advantages compared to conventional radar systems which include rapid prototyping and facilitating quick reconfiguration of different bands and parameters [139]. However, a main drawback of passive radars, which is not limited to just WiFi is that reflections off a target can be overpowered from the strong signal directly received from the transmitter of opportunity. Nonetheless, proper processing techniques, e.g. CLEAN algorithm [135,139], have enabled interference cancellation for target detection and localisation amid adversities even in indoors [137]. Consequently, a range of solutions targeting different applications have emerged including security and surveillance [135,139], tracking humans, man made objects and vehicles [136,138,153]. Interestingly, Wi-Vi [154] leveraged passive bi-static radar to track and recognise gestures using an *ISAR* in a through-wall setting. This technique significantly reduces the number of antennas by using the target's movement to emulate an antenna array.

6. Qualitative comparison of different schemes

In this section we first provide a concise summary of different categories of localisation technologies in general and compare their strengths and weaknesses in Table 2. We also illustrate the type of applications each technology targets, in conjunction with the corresponding publication. An important observation we made regarding technologies such as RF tomography, radio grids, RF fingerprinting, and radar to some extent is that they all target similar applications. Therefore the usability mainly depends on the strengths, weaknesses and the limitations of each technology.

Motivated by this, for each technology, we chose the publications that we perceived as the best considering properties that are important and consistent in all the solutions. The intuition is that by comparing the best solutions we can get an indication of the boundaries of the respective technology in practice. The properties were selected to include the dimensions (time, space and occupants) that illustrate the resolutions that were highlighted in Section 1 as well. The selected properties are as follows:

- Location error.
- Maximum no. of people simultaneously located.
- Number of devices required.
- Area size.
- Hardware cost.
- Calibration efforts.
- Scalability.
- Latency.

In Table 3, we compare the selected solutions. An adversity that we encountered during the comparison, however, is the lack of standard evaluation parameters and environments used within the research community. Most experiments were conducted in custom, controlled environments. For example in Table 3 we observe that,

(1) Authors provide the accuracy as either mean, median, min, max or root mean square error where each metric has its own pros and cons but does not necessarily convey the full picture of the experiment.
(2) The environment that the experiments were carried out (LoS/nLoS, cluttered/uncluttered) has a major impact on the accuracy.
(3) The compared schemes are across different fields and the accuracies may depend on the intended applications.

The performances of the schemes cannot be compared based on the numbers alone without standard metrics or settings, thus, we resort to a qualitative approach based on a three level scale. Accordingly, the table cells are coloured in three hues *green, yellow* and *red* to highlight *strong, moderate* and *weak* characteristics of the chosen schemes.

From Table 3 it can be observed that among existing technologies for human positioning, the systems that have least weaknesses are those that are based on Wi-Fi CSI and FMCW radar. However, the scalability of FMCW radar for large indoor environments (for some applications that are advertised such as elderly monitoring, appliance controlling and intrusion detection) is questionable due to hardware costs, large bandwidths and increase in antenna array size with the number of people (this leads to space constraints). Unless a compact SoC solution is developed, the hardware costs will be a challenge. On another perspective, radar technology has some critical challenges that has made this technology inaccessible for much of the research community: (i) requirement for special expertise e.g. antenna, RF front end design, (ii) the unavailability of standard system-on-chip solutions, (iii) the extensive signal processing phase to extract features, and (iv) hardware cost. However, it must also be highlighted that with the advent of software defined radios this issue has resolved to some extent.

In contrast, Radio grids and RF tomography have been tested in practical indoor environments (with large area sizes) with good accuracies. These technologies benefit from commercial devices and the signal descriptors are easily accessible (RSS and CSI), thus, researchers can focus on the problem itself. Especially, the low power TelosB motes can be deployed in large numbers to extend the range, whereas, WiFi is ubiquitous. Additionally, the introduction of fine grained CSI has reduced the number of devices significantly.

It is also noticeable that Ambient FM and UWB are the least developed among the compared with respect to the intended applications. Ambient FM is mainly constrained by not relying on dedicated transmitters, where the ambience is susceptible to change. It is evident that *Ambient Field Sensing* is at an early stage compared

Table 2
Strengths, weaknesses and targeted applications of respective technologies.

Technology	TX-RX	Strengths	Weaknesses	Targeted applications
RF tomography	IEEE 802.15.4 (RSS)	RSS is readily available, can use commercial hardware, existence of accurate models for.	High density of TX-RXs ⇒ cost & deployment efforts, low granularity of RSS ⇒ low resolution, TX-RX placement.	Intrusion detection, elderly care [31,63], rescue missions [155], border control [156].
Radio grids	IEEE 802.15.4 (RSS)	RSS is readily available, commercial hardware.	Low granularity of RSS, low model accuracies, high density of TX-RXs, TX-RX placement.	Intrusion detection & elderly care [157].
	IEEE 802.11n (CSI)	Commercial hardware, diversity of CSI streams, fine grained than RSS, WiFi is ubiquitous, long range than TelosBs.	Phase randomness, modifications to driver and firmware.	Elderly monitoring [3,44], vital sign monitoring (sleep apnea [1], respiration), intrusion detection, analysing shoppers behaviour [7], smoking detection [92], speech recognition [158], gesture recognition [94–97], occupancy detection [76–81,83] and people counting [58].
RF Fingerprinting	IEEE 802.11& 802.15.4 (RSS, CSI)	Commercial hardware, ubiquity of WiFi.	Calibration & training overheads.	Intrusion detection, border protection, low-cost surveillance, smart homes automation [159,160], building occupancy statistics [160].
RF backscatter	RFID readers and tags (RSS)	Commercial hardware, high spatial resolution due to high density of tags, range (10m), low training overhead.	High cost of RFID readers (€ 400-2000), deployment efforts of multiple tags.	Virtual touch screen [119], as elderly people surveillance [117], intruder detection [117], gesture recognition [117].
Ultra wideband	FCC-compliant UWB radios	High ranging resolution, high level of multipath resolution, obstacle penetration, low training overhead, fast processing.	Hardware cost (≈ € 1000), low range, hardware and antenna design.	Vital sign monitoring [126], rescue operations [155].
Millimeter wave radio	SDR	Commercial hardware, high accuracy (sub mm).	Very low range (1m), hardware cost,	Wireless transcription [127], virtual trackpad [127].
Radar	CW (SDR)	High precision in relative displacement measurement.	Hardware cost (≈ € 2000), a single radar cannot detect range, antenna and RF front end design.	Vital sign monitoring (respiration)[143], gesture recognition [149].
	FMCW (SDR)	High spatial resolution, accuracy (dm level), high range (10m), fast signal processing.	Hardware cost (≈ € 2000), antenna and RF front end design.	Elderly monitoring [27], vital sign monitoring (breathing, heart rate) [4], gaming [8], virtual reality[8], rescue missions [8], intrusion detection, controlling appliances [8,144].

to other areas. It is also understandable that there are many challenges in *Ambient Field Sensing*, including extensive fingerprinting, coarse-grained and fast deterioration of the fingerprint.

7. Trends, future research directions, challenges and limitations

In this section, we discuss some of the important observations we made during the review of the state of the art. The research we studied are the quintessential of the current generation of IDFL schemes. Section 7.1 summarises the trends and future research directions observed among these schemes and Section 7.2 summarises the existing challenges and limitations among them.

7.1. Trends and future research directions

(i) **Robustness under environmental irregularities.** Localisation techniques are generally calibrated and tested under a particular environment setting. Sudden changes in the environment such as furniture alterations can change the indoor radio channel and thereby impact the overall accuracy. However, we are beginning to see efforts on eliminating environmental effects by characterising the rate of path length changes to human motion [91] and Doppler shifts [56] particularly in activity recognition.
Another aspect is the output of these systems under the influence of domestic pets and other natural disruptions. To the best of our knowledge, there has not been any study on the impact of pets on the accuracy of RF localisation techniques.

(ii) **Drive for errors below decimetre levels.** A notable trend particularly among radar-based localisation is the drive for low positioning errors [8,27,116,117]. Notwithstanding the fact that 10 cm errors are a great achievement in a device-free context, for real-world applications such as indoor climate control, intrusion detection, elderly monitoring or rescue operations these are extravagant numbers. Apparently, there is a lack of communication between localisation communities and ubiquitous computing and context-awareness communities.
It is also not clear how errors as low as 10 cm can be achieved in a device-free setting. As even an average human being can occupy a ≈ 0.5 m^2 area. Due to the peculiarities and the range of sizes of the human body we argue that these positioning errors can be biased and replicating the same measurements in other settings can be challenging.

(iii) **Effective feature extraction.** There are open problems that are unique to CSI due to its structure. Recall that CSI is the frequency response of a channel. A commodity chipset provides 30 pairs of subcarrier amplitudes and phases for a single antenna pair. The amplitude provides information on the distance of the link through attenuation, however the attenuation is not constant along all the subcarriers due to frequency selective fading. LiFS [44] attempted to filter the dirty subcarriers (affected by fading) recognised through their model and inferred the positions of humans. To solve the same problem [91] and [80] resorted to dimensional-

Table 3
Comparison of selected features from best available technologies.

	Technology (*Measure*, *Transceiver*, Frequency)	Reference	Error (cm)	Max. people	Devices	Area (m^2)	Hardware Cost	Calibration	Scalability	Special characteristics
Wireless Networks	**Radio Grids** (*RSS*, *Chipcon CC2420* 2.4 GHz)	[75]	98[a]	2	23	64				Uncluttered indoor, targets ≤ 2 m apart, latency: 0.26 s
		[161]	94[a]	4	63	300				Uncluttered indoor, targets 5 m apart on average
	(*CSI*, *AoA*, *WiFi*)	[88]	62[c]	1	4	51.8				nLoS link, cluttered environment, LoS link 5 m apart on average
	(*CSI*, *WiFi*)	[44]	60[c]	2	11	150				nLoS link, cluttered home environment, AP, client locations are known in advance, latency:0.065 s
	RF Tomography (*RSS*, *802.15.4*, 2.4 GHz)	[6]	30[a]	1	30	70				Similar error in cluttered indoors and in through-wall
		[162]	55[a]	4	33	58				Cluttered indoor, no. of targets unknown a priori, their paths can intersect, real-time operation
		[163]	80[b]	4	24	84				Cluttered and through-wall uncluttered indoors
	RF Fingerprinting (*RSS*, *802.11b*, 2.4 GHz)	[164]	250[c]	1	4	140				Cluttered indoor, minimum detection F-measure 0.93
		[107]	256[a]	3	2APs & 3MPs	130				Latency 2.56 ms, 100 % estimation of occupants within 1 entity difference
	(*RSS*, *802.15.4*, 2.4 GHz)	[72]	130[a]	4	22	150				Cluttered indoor, 86 % overall counting percentage up to 4 people
	Ambient FM (*RSS*, *SDR*, 87–111 MHz)	[113]	96[d]	1	1	18				Coarse-grained positions, accuracy degrades over time ($\approx$1 m in 5 days)
	UWB (*ToF*, *FCC-compliant UWB radios*, 3–5.5 GHz)	[126]	12–180	1	4	15				100% presence detection, no need of training, deployable in cluttered areas
	RF Backscatter (*RSS,ToF,AoA*, *SDR with WiFi PHY*, 2.4 GHz)	[116]	12[e], 80[f]	5	1	56				Resolves humans 0.5 m apart or more. With 5 radios errors reduce to 7 cm and 70 cm respectively
	(*RSS*,*RFID tags and reader*, 800–900 MHz)	[117]	x=7.8[c] y=20[c]	1	1 reader &45 tags	28				Cluttered indoor, through-wall (5" hollow wall and 8" concrete wall), performs gesture recognition
Radar	**FMCW** (*Doppler shift*, *ToF*, *SDR*, 5.46–7.25 GHz)	[27]	x=10[a] y=13[a] z=21[a]	1	1	30				LoS 3D and gesture recognition of moving targets
		[8]	11.7[c]	5	1	35				Tracks 4 mobile and 5 static users,radar range:10 m
	FMCW, CW (*Doppler shift*, *ToF*, *SDR*, 5.8 GHz)	[149]	10[g]	1	1	60				The interferometry mode detects stationary person from vital signs and FMCW mode detects absolute range of the person. Cluttered, indoor environment.

AP: Access Point, MP: Monitoring Point, [a] Mean error, [b] Root- mean-square-error, [c] Median error, [d] upper bound of 90% errors [e] Mean error for moving objects, [f] Mean error for stationary objects, [g] Maximum error.

ity reduction techniques, linear (PCA) and non-linear (kPCA), respectively. The intention is to efficiently extract features from multiple streams of CSI. However, in these two approaches the attenuation of CSI is lost, therefore the extracted features can only be used for occupancy detection, activity and gesture recognition.

(iv) **Deep learning for human sensing.** Unlike traditional machine learning algorithms that require manual feature selection and definition of rules, deep learning is able to learn the correct features and make the right predictions. Moreover, recently, deep learning techniques have been successful in a variety of fields including computer vision and speech recognition which have similar data modelling challenges to human sensing such as noise in data and class diversity [165]. Following this trend, there has been some progress in application of deep learning to activity recognition using RFID in device-based localisation [166] which can be easily adapted to device-free activity recognition as well.

(v) **TX-RX frequency synchronisation.** Precise estimation of the carrier frequency offset is a major challenge faced by low cost narrowband COTS transceivers which leads to phase randomness of the received signal. Phase randomness not only restricts accurate channel estimation for localisation, it also impedes measuring the Doppler shift of the received signal. Recently Luong et al. [167] introduced a platform to frequency synchronise the transceivers and were able to achieve a frequency difference of 0.1Hz for a transceiver operating at a centre frequency of 434 MHz.

(vi) **Vital sign detection for human detection and localisation.** Despite the potential of RF to locate static people, most schemes still rely on motion for presence detection. Currently, there are a few instances of detecting presence through vital signs such as heart beats [143] or breathing [4], [77] but those are primarily constrained by range limitations and clutter. Hence, there is an apparent need among presence detection techniques to increase the effectiveness in these schemes for real-world situations (e.g. office environments in which people tend to stay static most of the time).

Table 4
List of acronyms.

Acronym	Definition
AoA	Angle of Arrival.
AP	Access Point.
API	Application Programming Interface.
COTS	Commercial Off The Shelf.
CIR	Channel Impulse Response.
CSI	Channel State Information.
CT	Computed Tomography.
CW	Continuous Wave.
DFCW	Differential Frequency Continuous Wave.
DVB	Digital Video Broadcasting.
FCC	Federal Communications Commission.
FFZ	First Fresnel Zone.
FM	Frequency Modulated.
FMCW	Frequency Modulated Continuous Wave.
GSM	Global System for Mobile.
HMM	Hidden Markov Model.
ID	IDentification.
IDFL	Indoor Device Free localisation.
IQ	In phase-Quadrature.
ISAR	Inverse Synthetic Aperture Radar.
kNN	k-Nearest Neighbour.
LoS	Line-of-Sight.
LQI	Link Quality Indicator.
LTE	Long Term Evolution.
MIMO	Multiple Input Multiple Output.
MUSIC	MUltiple Signal Classification.
nLoS	non Line-of-Sight.
PCA	Principal Component Analysis.
PDF	Probability Distribution Function.
PLR	Packet Loss Rate.
RF	Radio Frequency.
RFID	Radio Frequency IDentification.
RSS	Received Signal Strength.
RTI	Radio Tomographic Imaging.
RX	Receiver.
SBC	Single Board Computer.
SFCW	Stepped Frequency Continuous Wave.
SDR	Sofware Defince Radio.
ToF	Time of Flight.
TX	Transmitter.
UWB	Ultra-Wideband.

7.2. Challenges and limitations

(i) **Deployment overheads.** A concern in common with all technologies is the deployment overhead in terms of time and labour effort. This becomes even more complicated in *Fingerprinting* approaches. In respect to the initial transceiver deployment, *RF Tomography* and *Radio Grids* using TelosB motes and RFID require the most sensing devices, 30–40 for a 70 m^2 area, to obtain good accuracy (accuracy of <1m). *RF Fingerprinting* and *Radio Grids* with WiFi devices require fewer sensors, in the range of 5–20 for a similar area depending on the type of radios being used. Hence, deploying such high density of transceivers in multiple rooms will be demanding in terms of labour and cost. If these devices are battery-powered, maintenance and energy requirements will be additional issues in the long run.

(ii) **Building energy consumption.** Another complication with the deployment of hundreds of transceivers and Single Board Computers (SBCs) in a building will be the effect on overall energy consumption of the building. It may turn out for example that the energy savings achievable through the use of occupant detection based climate and energy control may in fact be cancelled out by the increased energy usage due to the localisation and occupancy detection system.

(iii) **Hardware and maintenance costs.** Among the fine-grained localisation solutions, UWB transceivers used to be extremely expensive but are now reaching more modest cost levels. As an example, a development kit with four transceivers is around € 1000 while a standalone transceiver is around € 15.
Advanced military radar systems with costs in the range of tens of thousands of euros [117] are out of the scope of civilian applications, however, alternative solutions such as SDR-based radars and Wi-Fi APs provide very good accuracies. The initial cost for prototype development is significantly reduced to €1000–2000. The cost of an SDR primarily depends on its bandwidth, and the bandwidth is related to the overall accuracy. In this context, device-free RFID is also a reasonable option with costs of readers ranging from €600–2000 and tags at 15 cents [117].
Considering other low cost options, deployment of a multitude of € 90 TelosB motes (e.g 30 in a 70 m^2 area [6]) in *Wireless Networks* ultimately result in costs in the range of € 2700. Despite this, higher volumes of purchases will likely reduce costs if there is real world uptake, even though, maintenance costs will still remain. Considering these facts, localisation schemes that employ COTS Wi-Fi chipsets costing as low as € 10 and included in SBCs are the most cost-effective among the current solutions.

(iv) **Interoperability with other appliances**. *Wireless Networks*, especially, use frequency diversity as a strategy to increase the localisation accuracy. These devices typically operate in the Industrial, Scientific, and Medical radio band

(ISM). An issue that naturally occurs with high densities of transceivers in *Wireless Networks* that use frequency diversity in indoor environments is the interference to other nearby wireless devices (e.g. commonly used Wi-Fi devices such as laptops or smart phones).

(v) **The threat on privacy and security.** A major advantage of RF-based localisation over computer vision is the increase of occupant privacy. However, recent advances in presence detection, activity or gesture recognition schemes present a new kind of threat especially for Wi-Fi users. Intruders can exploit the pervasiveness of Wi-Fi installations in extracting key information about occupants such as their time of presence during the day or involved activities which can be useful intelligence for criminal purposes [168].

(vi) **Scalability to large crowds and indoor spaces.** It is noticeable that the maximum number of simultaneously located persons is less than six among all aforementioned schemes. This is an acceptable number for small rooms and office cubicles. The area size for the most successful method (in terms of the number of users detected with good accuracy) is merely 56 m^2 [116]. For real-world applications that involve large crowd gatherings such as exhibition centres, shopping malls and conferences, it is apparent that none of those methods are scalable in their current state. Potentially, technologies like *FMCW radar, Backscatter or Wi-Fi CSI* may exceed these numbers in the future (Table 4).

8. Conclusion

This article analysed the current progress in RF-based indoor device-free localisation giving precedence to indoor positioning. We analysed the literature by decomposing the localisation dimensions into occupants, space and time. We also included a detailed taxonomy and a comprehensive review of the localisation techniques. We evaluated the respective technologies qualitatively, discussed trends, limitations and also indicated several future research directions. Based on the review, we also identified some emerging device-free localisation technologies.

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Sameera Palipana received his B.Sc. (Hons) degree in Electronic and Telecommunication Engineering from University of Moratuwa, Sri Lanka, in 2010. He received his M.Sc. degree in 2014 from University of Bremen, Germany and is currently a Ph.D. Candidate in the Department of Electrical Engineering at Cork Institute of Technology, Ireland. His research interests are in the areas of device-free localization, signal processing and data analysis.

Bastien Pietropaoli received an engineering degree with a specialization in nuclear engineering at Mines de Nantes, France in 2010. He was awarded his Ph.D. in computer science in 2013 at Universit de Rennes 1, France. He worked for three years on a smart home project in the team ACES at INRIA Rennes, France and in collaboration with EDF R&D. His research interests are Ubiquitous computing, smart home, context-awareness, sensor data fusion and belief functions theory.

Dirk Pesch is a professor and the head of the Nimbus Centre for Embedded Systems Research at Cork Institute of Technology, Cork, Ireland. Nimbus carries out research and innovation in Cyber-Physical Systems and the Internet of Things with applications in energy and water resource management, health and assisted living, smart cities and the built environment. Dirks own research interests focus on architecture and design of low power wireless networks and services for the Internet of Things and interoperability issues associated with the IoT applications. He has over 25 years research and development experience in both industry and academic and has co-authored over 180 scientific articles. Dirk is involved in national research initiatives such as the CONNECT Centre and many EU funded research projects, including as coordinator. He is involved with two startups and contributes to international conference organization in his area of expertise. Dirk received a Dipl.Ing. degree from RWTH Aachen University, Germany, and a Ph.D. from the University of Strathclyde, Glasgow, Scotland, both in Electrical & Electronic Engineering.