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Ubiquitous Localization (UbiLoc): A Survey and Taxonomy on Device Free Localization for Smart World

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***Abstract*—The 'Smart World' envisioned by technology will be achieved by the penetration of intelligence into ubiquitous things including physical objects, cyber-entities, social-elements or individuals and human thinking. The development of Smart World is enabled by diverse applications of Wireless Sensor Networks (WSN) into those components identified as things. Such a smart-world will have features controlled significantly by the location information. Control and Policy information of Smart World services, often addressed as Location-Based Services (LBS), are governed by location data. Localization thus becomes the key enabling technology for Smart World facilities. It is generally classified as active and passive techniques in nature. Active localization is a widely adopted localization scheme where the target is detected and tracked carries a tag or attached device. The other category, Passive methods, defines targets to be localized as free of carrying a tag or device, hence also referred to as Device-Free localization (DFL) or Sensor-less localization. The passive approach is a well suited for the development of diverse smart world applications with ubiquitous localization. Device-free localization schemes fall into a wide range of application scenarios within the Smart World ecosystem. A few notable examples are occupancy detection, identity definition, positioning, gesture detection, activity monitoring, pedestrian and vehicle-traffic flow surveillance, security safeguarding, ambient intelligence-based systems, emergency rescue operations, smart work-spaces and patient or elderly monitoring. In this paper, the revolution of device-free localization technologies have been reviewed and classified comprehensively. Further, the emergence of the Smart World paradigm is analyzed in the context of device-free localization principles. Moreover, the inherent challenges within the application domains have been extensively discussed and improvement strategies for multi-target localization and counting approach are discussed. Finally, current trends and future research directions have been presented.**

***Index Terms*—Device Free Localization (DFL), Radar, Tomography, Fingerprinting, Scattering, Smart World**

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I. Introduction

THE location of an object and reference time-frame are two vital variables of any engineering or scientific observation. Any reading extracted from an intelligent system is fundamentally associated with the location and time values of the corresponding object or event. The inception of Localization techniques had begun in the early days of human civilization, as in reference frames based on the relative positions of heavenly bodies (sun, moon, and stars) for navigation on the ground and in the ocean. Later on, finer techniques were developed based on the Earth's magnetic field, for instance, the compass. With the onset of the industrial revolution the earliest precise measurement of time using the atomic clock was developed, and later came location identification from the Global Positioning System (GPS)[1]. GPS accuracy lies within tens of meters under ideal conditions, and was commercialized in the 1990s. The localization technology stream further developed around outdoor[2][3] and indoor[4][5] use-cases with accuracy scales in the range of meters. Finally, the category of device-free approaches to localization principles were applied in the medical field for tumor detection[6], which was highly precise[7] and accurately measuring in the range of millimeters [8][9]. Figure 3 represents the evolution of different approaches of device free localization scheme.

The emergence of location-based services and applications has led to a growing demand of ubiquitous localization or localization anywhere [10], [11], [12], [13]. Wireless devices and Wireless sensor network technologies and applications being applied into widespread scenarios have gained much interest in recent years. The localization principles for devices in these networks have captured constantly growing attention of the R and D community. Live monitoring, tracking and activity detection of objects and entities are the most frequently executed operations. Existing localization techniques from relevant literature can be categorized as either Active or Passive models. Active localization scheme is the method of having the device located by the system using an embedded sensor, an RFID tag or an electronic device [14]. The principle also takes to use major systems such as Global Positioning System (GPS), infrared-based and ultrasonic-based ranging systems. Passive localization, on the other hand, is based on the device or thing (object) tracking without having to resort to embedding any electronic device. In other words, this principle is valid in scenarios where the object is localized without any

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information from or the presence of any localization system. Relevant scenarios most commonly encountered in the real-world are intrusion detection in buildings, secure facilities or private properties, specifically within the National Defense sector or security domain, active online traffic monitoring of a Smart City, localization of human activity in a specified geographic region, health care monitoring, telemetry systems, etc. Hence, a vast array of research interests are steadily evolving in the device-free localization or sensor-less localization front [15].

To elaborate on this flexible mechanism, device-free localization methods utilize object-to-object interactions defined through radio signal properties like absorption, scattering, diffraction, reflection, refraction or any rational combination of these techniques. The radio link modification due to the physical and geometrical properties of the object under observation are perceived in the region-of-interest (ROI), leading to the object being localized precisely in real-time. In building automation systems, like the smart home or smart building, occupant presence detection and counting are keys to numerous applications like identity detection, gesture monitoring or activity monitoring in living entities.

However, these functions, when designed in the context of a smart home, hardly take into account occupancy information [16], leading to a significant amount of energy wastage in these automation systems. Proper occupant detection inside a building can automate the building for low energy consumption [17], [18], [19], [20], [21], [22]. Device-free localization methods also offer logical support to consumer applications such as fitness tracking [23], [24] and monitoring of the elderly [25], [26] in health care services. Other notable applications include gesture recognition in gaming [27], intrusion detection [28], border security assistance [29], security safeguard, road side and traffic flow surveillance, emergency rescue operations, ambient intelligence schemes, smart spaces and patient monitoring. In all the aforementioned scenarios, the object is not committed to carrying an electronic sensor for localization, which shows an important research area over traditional active methods of localization [30].

Interrelationships between localization techniques and smart world application domain are essential and interconnected [41], [42]. The smart world paradigm can be thought of as consisting of four layers - the physical world, the social world, the cyber world, and the thinking world. The physical world is a mixture of people and things (objects) and the context of their encounters and interactions. All of these levels have a critical requirement to gather information on the location of people and things, with respect to time and physical displacement. Smart vehicles and self-driving vehicles, autonomous systems in manufacturing, communication, etc. epitomize the vitality of need for location information in geographic navigation in the physical world. Social behavior and inter-relationships among identifiable entities are analyzed within the social world background. Location-based gaming and the spread or influence of epidemics are two typical social events that require location information for the progress and continuation of social activities [43]. Localization and tracking are equally important in the cyber-world domain for real-time

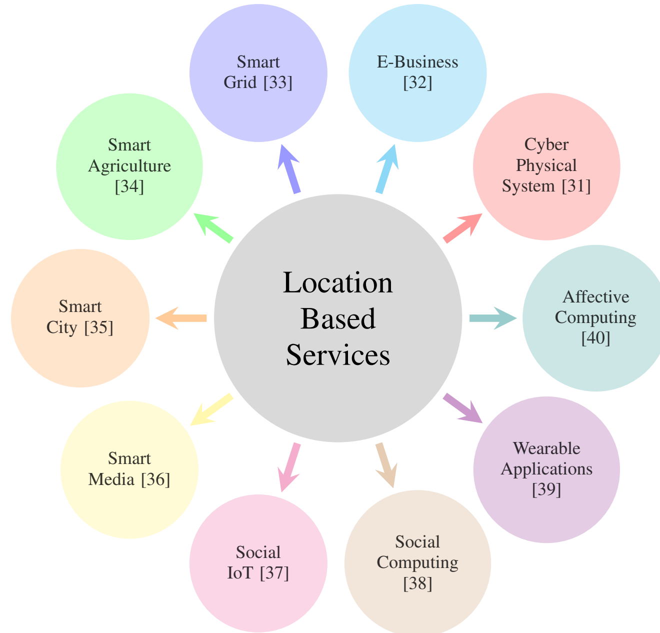

Fig. 1. Location Based Services(LBS) In smart World

applications like location-specific web search to render cyber-world intelligence. Finally, the thinking world applies location information in many aspects of life, like travel, residence, career, education, and entertainment, to render better quality-of-life for human beings. Therefore, the services for smart World are impossible to design and establish in the absence of location information. A high-level outline of the location-based services described here are presented in Figure 1.

Depending upon the technologies incorporated, like optics, electrical or magnetic field variation, radio frequency, infrared or mechanical principles, etc., device-free localization can be classified into different domain technologies. Optical or infrared methods use the highest frequency range. These methods rely on computer vision technologies for localization, but they cannot overcome wall penetration, darkness, atmospheric smoke, [44] etc. Further, these methods have privacy issues as they visually monitor, using cameras, individuals [45]. Electrical field or mechanical pressure sensor based localization has given the best results to date, but the deployment cost is much higher in comparison to other methods [46], [47]. The main advantage of radio frequency based device-free localization is that it overcomes the problems of physical barriers (walls), lack of clarity in vision, range and accuracy trade-offs and privacy. Typical measures used in radio frequency based device-free localization (DFL) are designed to include Received Signal Strength (RSS), Time of Arrival (ToA), Angle of Arrival (AoA), Channel State Information (CSI) and Channel Frequency response.

In this paper, a thorough technical description of localization methods in connection to Smart World scenarios and valid explanations of the technical complexity, current trends, prospective applications, and future research directions have been presented. The multidisciplinary area of localization science with regards to device free sensor-less localization is

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extensively reviewed. The rest of the paper is organized as follows: The focus of Section II is to explain the evolution of various device-free localization (DFL) techniques. To simplify the understanding of different localization methods, a detailed taxonomy is presented in Section III. We then discuss the key classes of localization techniques in Section IV to VII, with a focus on the critical analysis of the existing approaches. One of the key features of this tutorial paper is to learn critical lessons from the different classes of localization techniques, the later is discussed in Section VIII. Section IX describes the application of DFL with a focus on analyzing its core technical issues and challenges. Some discussion on future research directions is also covered in Section IX. Finally, the conclusion is presented in Section XI.

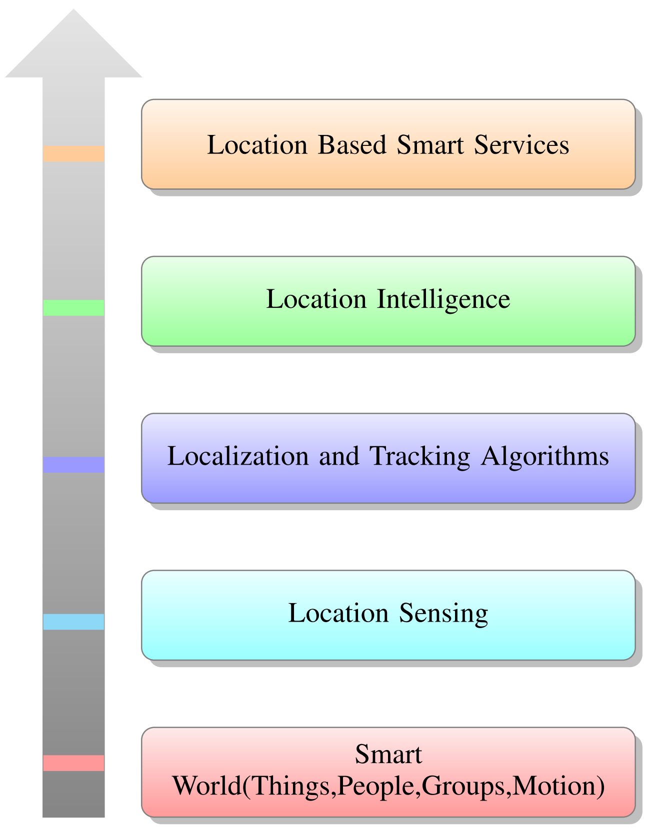

Fig. 2. Layers of Ubiquitous Localization System for Smart World

II. Emergence of Device Free Ubiquitous Localization Techniques

The inherent need for position and location knowledge demands diverse research initiatives into localization technologies. Due to the pervasive presence of wireless signals around us (e.g., WiFi, GSM, and FM radio), wireless localization can be thought of as the most prevalent technique to implement location estimation. Over the years, various wireless localization techniques have been successfully developed. They have also evolved from active to passive in nature based on radio frequency based communication techniques. Priyadarshini et al.[59] have categorized localization as having two types - active and passive - on the basis of presence of the radio frequency tag. One of the most popular active localization system was developed around 1960s for military applications called Global Positioning Systems (GPS), explained by Youssef et al.[60]. GPS became the most popular referencing system for almost every positioning and navigation application. However, it has severe limitations in indoor scenarios [61]. GPS has also been noted to start failing when there is attenuation or obstacles in line-of-sight ranging scenarios, like in a city with high-rise buildings, forests with high density and thick canopies, as well as mountainous areas, mostly due to link failure in establishing communication session from the GPS device to the satellite [61][62]. To overcome the above-described problems different approaches have been proposed for electronic identification. Radio-frequency based identification techniques have been gaining quite a bit of momentum based on their features of low power consumption and accuracy. The object to be localized have to carry identification tags which can store and process information in real-time for localization and tracking of the object [63].

Radio frequency based systems work by using three subsystems: identification tags, servers, and readers, as proposed by Bouet et al. [63]. The tag can be of three types - active, semi-passive and passive. Active RF tags carry batteries for power supply requirements. The passive tags don't have any internal power systems [64], instead, they communicate with the readers by backscattering the carrier signal received and bringing electromagnetic resonance into the picture [61],[63]. Semi-passive tags have batteries powering up their systems as well as apply the backscattering method. This radio frequency method of localization is highly accurate and less costly but in a real-time application, it has the limitation of multi-object tracking[59].

A newer human-centric design of localization methods are being adopted for healthcare and fitness tracking scenarios through the framework of Wireless Body Sensor Networks (WBSN) [65]. WBSNs are constituted of base sensor nodes for telemetry (generally wearable devices) and central processing node(s) for further analysis. The wearable sensor nodes collect physiological and functional information of the human body which is then processed by the central node to generate intelligence required to manage the operations, control the functions and schedule the wearable devices. Nonetheless, a major problem exists within the scope of these systems - the interference of sensing signals while the users are closely located [65]. Further, a Slotted Carrier-Sense-Multiple-Access with Collision Avoidance (CSMA/CA) based Hopping method is used in WBSN to mitigate the interference.

Device-free localization or sensor-less localization is a growing generic research interest in the domain of real-time human and object detection across a multitude of applications such as health care system, logistics, security and defense, manufacturing and production and asset tracking, etc. [66]. Such an approach employs the different environmental radio changes for deriving logical rules for tracking entities. These methods, therefore, work without any active sensor unit embedded in for the localization of objects [67]. The presence of human entities is reflected in the physical phenomena that are

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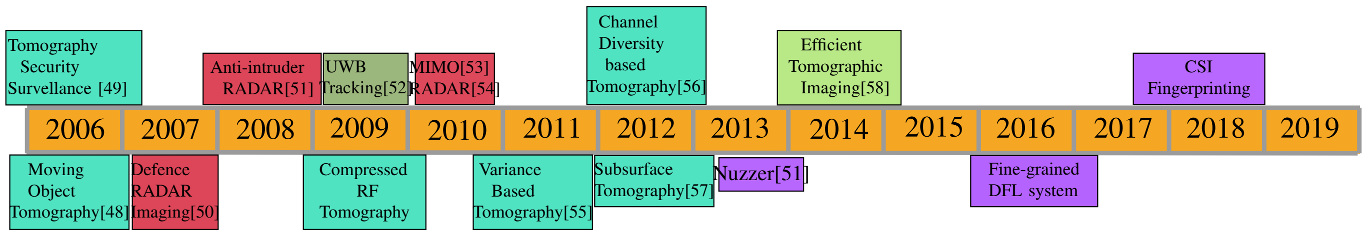

Fig. 3. Emergence of Device Free Localization System for Smart World

associated with the signal change due to shadowing, diffraction or scattering. These phenomena continuously change the magnitude and phase of the signal which can then be adopted for localizing individuals. These changes arise in the scattered signals due to the variation of density and composition across the cross-section of the human body [68]. Several algorithms and models have been proposed in the literature for signal pattern detection and extracting location information. However, it is quite difficult to compare those methods since they vary in terms of region of deployment, hardware configurations, type of communication protocols used, and so on.

The human presence detection inside an indoor environment is another area of growing interests and device-free localization techniques promise to provide good solutions. The wireless link between the sensor node and the associated signal strength variation provide a strong clue toward localizing the human entity. Priyadarshini et al.[59] considered the resonating properties of water to the signal shadowing effect. The author asserts that over seventy percent of the human body composition is water and taking the water's resonating properties into account for the development of device-free localization systems. El-Kafrawy et al. [68] developed a DFL system considering the RSS variation associated with human motion. The author designed a ray tracing model using a bunch of transmitters and receivers, and localized indoor humans based on the phase change of the line-of-sight signal. Jamie et al.[69] analysed the movement pattern of objects with respect to RSSI. The author conducted an experiment using wireless sensor networks and concluded that wireless attenuation of signals depended upon the number and speed of targets.

The main aim of this survey is to summarize the device-free localization techniques, which are required to realize smart world application. Although smart infrastructures including the internet of things and sensor/actuator networks are being actively investigated by the community, there is currently lack of literature that critically surveys and analyzes device-free localization methods. In depth study and critical analysis of the existing device free localization methods is one of the key contribution of this tutorial paper. [15], [59], [60], [61] by focusing a specific scenario. These approaches are limited and cannot focus the overall taxonomy of device-free localization context. Patwari et al. [15] considered measurement of RF sensors and took into account of the statistical estimation for location purposes. Another approach using database training of the tracked entity for localization is presented in [60], [70], [71]. Techniques for localization based upon physical parameters like the electromagnetic field reconstruction [72], narrow-band radar [73], tomography [49], [50],[48],[74] have also been designed and tested. MIMO radar based method [53] [54] uses spatial diversity for reliable detection. Ultra-Wide-band methods [15][75][51][52][76][77][78] are designed on the impulse response measurements for the separation of multipath changes and calculate time delay to estimate location. Image estimation methods like radio tomography [79][55][56] exploit RF measurements using spatial filters to estimate location and motion of tracked objects. Further, combined application of RF tomography and compressed sensing [80] for link measurement gives an energy efficient solution to the DFL problem. Accurate and robust human motion and activity detection by Wi-Fi signal is presented by Kosba et al.[81]. Device-free method of human occupancy detection is reviewed by Priyadarshini [59] and indoor active and passive localization methods have been analyzed by Deak et al.[66]. Figure 3 shows the evolution of device-free localization methods over the last 15 years. As the aforementioned methods focus on specific research problems, there is a requirement to undertake critical and comparative analysis of these methods, the later is the key contribution of this survey paper.

III. Classification of Device Free Localization Technique

The development of ubiquitous localization system is possible with the extensive use of wireless signals like GSM, WiFi and FM. These categories of Device-Free Localization (DFL) techniques are often referred to as radio sensing or sensor-less sensing. This method exploits link measurements to estimate object location. The primary properties of wireless links applied in radio-sensing are Received Signal Strength (RSS) and Channel State Information (CSI). There are two types of approaches which take into account the measured properties for location estimation: 1) Shadowing or Link Quality Measurement, and 2) Reflection or Scattering of the link. Hence the methods are also categorized as 1) Vision-based approach (uses shadowing or link quality measurement), and 2) Radar based approach (uses reflection or scattering of the link). The detailed taxonomic classification is given in Figure 4

A. *Radio Vision Based Approach of Device Free Localization*

Here, the variation in the properties of wireless links between the sensor nodes is exploited for location estimation. This can be based on either the physical layer values e.g. Channel State Information (CSI) or the higher layer measures e.g. Received Signal Strength (RSS). The logical model of a

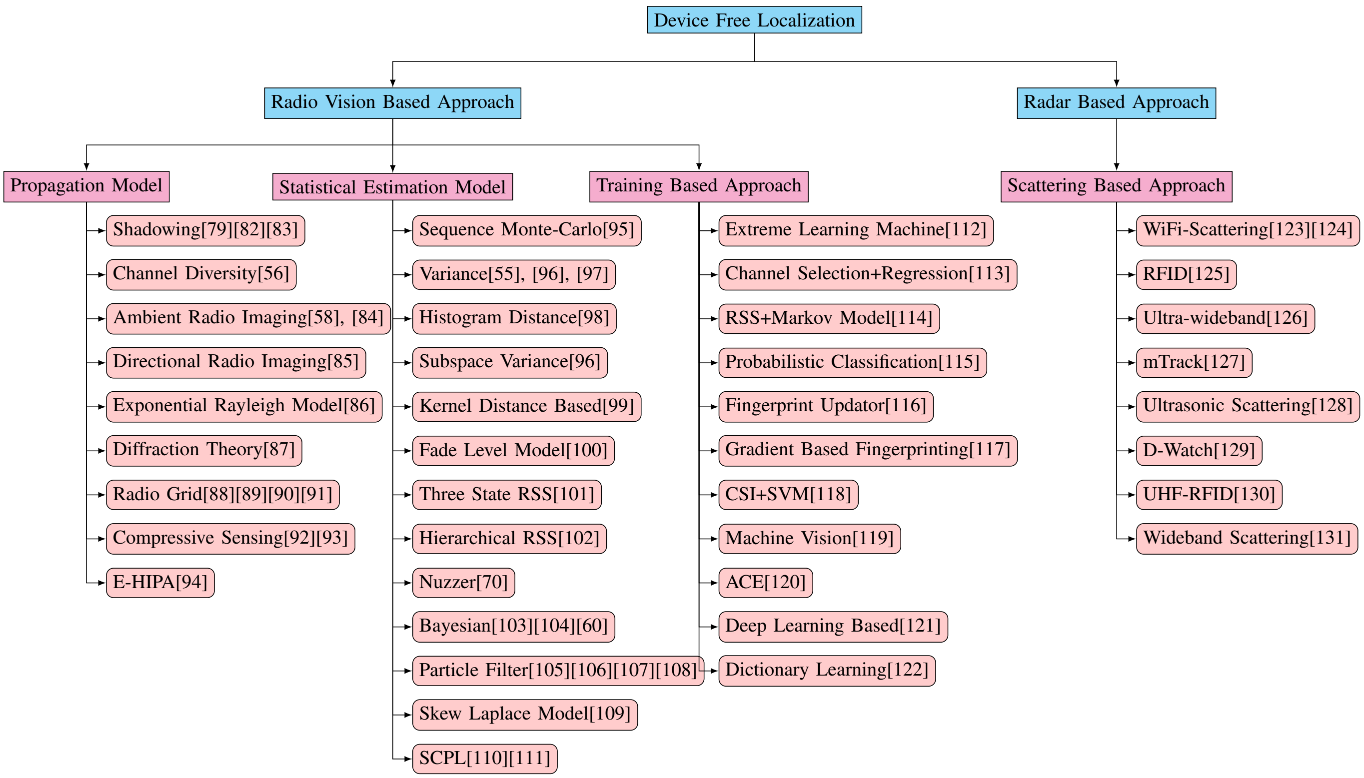

Fig. 4. Taxonomy of Device Free Localization

localization problem can be realized as an object interfering with wireless transmission links. Contextually, a transmission link comprises of periodic frames of adjacent symbols and an object in position x inside the link area performing an activity δ. The state of the object can be represented as a combination of its location and activity as $\Theta = [x, \delta]$. Channel response over a set of received symbols depends upon the object state Θ. In static environment conditions when the object is not hampering the link, $(\Theta = \phi)$, the equivalent channel response $h(\tau|\phi) = \Sigma_{k=0}^{N} \alpha_k g_{\tau-\tau_k} e^{-j\phi_k}$ is modelled as a multipath which is a combination of N delayed paths. Here, α_k and ϕ_k are the amplitude and the phase-shift of the k^{th} link respectively and $g_{\tau-\tau_k}$ models the received pulse waveform with delay τ_k. When an object is in state Θ, the changes in the channel response at symbol time $t\epsilon T$ may be represented as

$$h_t(\tau|\Theta) = \Sigma_{k=0}^{N} \alpha_k(t|\Theta) g_{\tau-\tau_k(t|\Theta)} e^{-j\phi_k(t|\Theta)} \tag{1}$$

where the amplitude $\alpha_k(t|\Theta)$ the phase shift $\phi_k(t|\Theta)$ and the augmented delay $\tau_k(t|\Theta)$ of the k^{th} link highlight the object-generated interference compared to the object free state $\Theta = \phi$ Amplitude $\alpha_k(t|\Theta)$ and phase shift $\phi_k(t|\Theta)$ incorporate object induced micro Doppler effects.

The above deduction proves that the presence or motion of an object induces a change in channel link quality of communication systems. The basic structure is shown in Figure 5, where the detection of objects is based on the extraction and estimation of the measured RSS or CSI values.

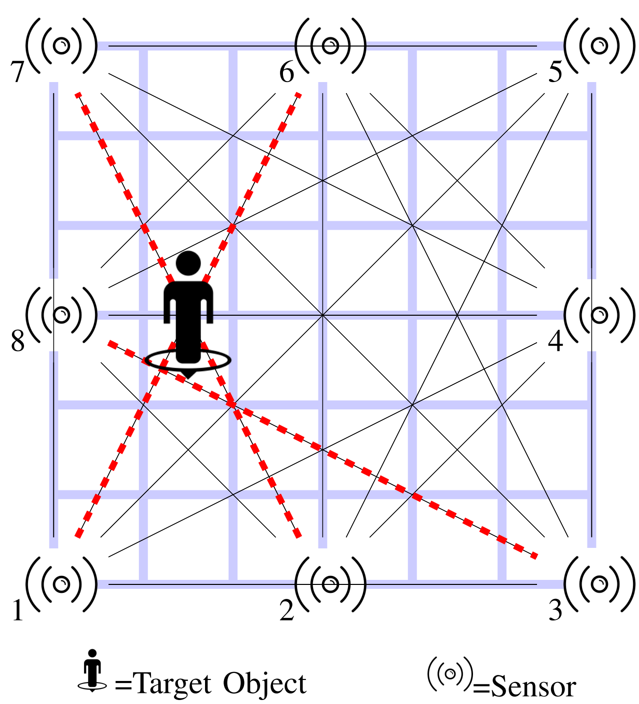

Fig. 5. Vision Based Approach of Device Free Localization

1) RSS: The most common metric of measurement of channel quality is the Receiver Signal Strength (RSS). RSS is commonly used for transmitter (TX)-receiver (RX) link adaptation and link measurement for the different estimation. Power estimator or peak detector is widely used to acquire information about signal strength.

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2) CSI: Channel State Information (CSI) is a metric of channel response induced due to some interference in link level. CSI estimation is obtained from a reference training signal multiplexed with information symbols. Hence, in contrast to RSS, the CSI information processing gives multiple independent measurements and can be used to localize and track fast object motion and activities.

$$H = (H_{ij})_{N_{tx}.N_{rx}} \quad (2)$$

H_{ij} is the CSI of the link formed by TX_i and RX_j containing information of the N subcarrier.

Radio vision method maps changes in link properties of the region of interest with respect to the estimated location. These approaches are further categorized as 1) Training based, and 2) Model-based approaches of Device-Free Localization. To compute the location by training based approaches, an off-line training-phase free from the object is a prerequisite. A Model based approach is further sub-divided as Propagation Model methods and Statistical Estimation Model methods, which do not require an off-line training phase.

B. Radar Based Approach of Device-Free Localization

A Radar-based approach of Device-Free localization exploits the scattering or reflection property of the radio link. This is modelled as n_p transmitter (TX)-receiver (RX) pairs operating as a network of sensor radars with each pair acting as an index. The index set is represented as $N_{p1} = \{1, 2, ..., n_p\}$. The i^{th} pair transmitter is in location $p_{tx}^{(i)}$ and emits a signal $s(t)$. The location of the receiver is $p_{rx}^{(i)}$, it received the signal after backscattering by objects or scatterers of the environment.

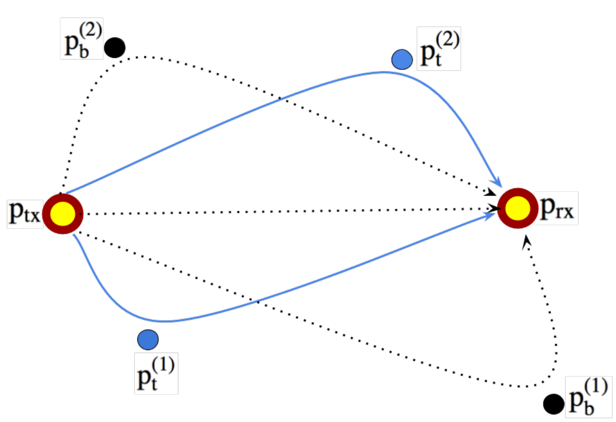

Fig. 6. Radar Based Approach of Device-Free Localization: A bi-static sensor radar model: Red empty circles represent the transmitter and receiver positions, blue circles represent the target scatterers, and black circles represent the background scatterers. Black dashed lines indicate the direct path between the transmitter and receiver as well as the first multipath component related to the background scatterers. Blue solid lines indicate the first multipath component related to the background scatterers

The sensor radars (SRs) are modelled as a random set N_t of n_t targets. The k^{th} target t_k is located in position $p_t^{(k)}$ with $k \epsilon N_t$. Further a random set N_b of n_b background objects is in position $p_b^{(k)}$ with $k \epsilon N_b$. The background objects are always present even in the absence of targets. Figure 6 shows a bi-static (One TX and One RX) sensor radar with two target scatterers and two background scatterers.

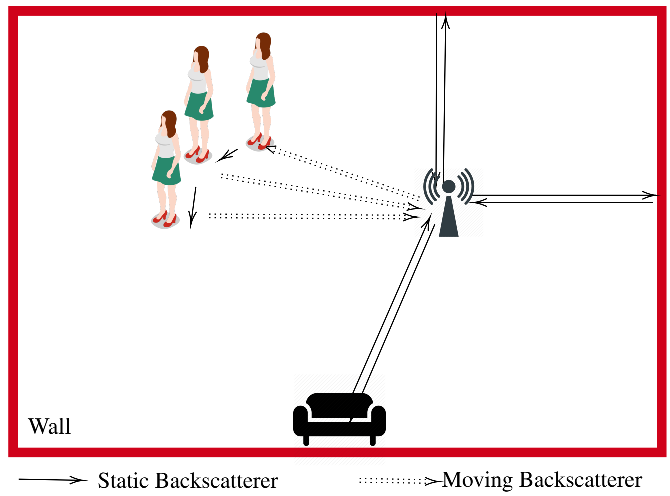

Fig. 7. Static and Dynamic Backscattering Model

A promising approach of device free localization, based on wide-band and ultra-wide-band (UWB) [132][133][134] signal sensor radars (SRs) is gaining popularity in applications like presence detection and counting of objects. The advantage of a wide bandwidth is the ability to achieve localization with high resolution, multipath mitigation and multiple target detection with closed position, etc. [135][136][137]. Multi-object counting and localization is achieved with the placement of UWB radar at the entrance of the region-of-interest based on the time of arrival (ToA) of back-scattered signals [138]. This algorithm relies on the threshold crossing of estimated ToA measurements. Choi et al. [139] had proposed a counting algorithm using local maxima of the power of the received signal. In his method, when a local maxima exceeds a defined threshold, a set of samples around the local maxima are deleted iteratively. However, this approach bears the limitation that the design of the proper threshold value which is crucial for the system performance [135].

Jin He et al. [140] proposed a crowd-centric counting algorithm based upon Support Vector Regression (SVR) to learn the relation between extracted feature and the number of target objects. The learning phase parameters depend on the training sequence derived from the feature set that belongs to both the time and frequency domain. However, in the above-mentioned research work, there is no clear explanation of the theoretical model that was used for localization and counting. A list of scattering algorithms for localization based on radar principle has been reviewed and categorized in the taxonomic trees as shown in Figure 4. The scattering model can be further static or dynamic in nature based on the tracked object as shown in Figure 7.

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IV. Propagation Model Based Device Free Localization

Device-free localization approaches exploit radio links and their properties within the sensor network domain for the estimation of object location. The RF sensor network is a network consisting of RF sensor nodes. Here, the RF wave parameters denote the various characteristics of sensing operations. In RF sensor networks the sensors broadcast and receive signals via wireless "links", which are projections of the sensor node passes in the region-of-interest using received signal strength (RSS) measurements. Any object that crosses these links interferes with the link and alters the measured RSS value of the link. The receiver senses and exploits those RSS variations for location predictions of the object. A proper propagation model of those links with RSS characteristics helps in the development of the localization technology domain. This section reviews state-of-the-art localization approaches based on the propagation model.

A. Propagation Models

1) Shadowing: Shadowing model exploits the RSS attenuation property of the radio link as shown in Figure 8. In this model, the environment is first considered without the localizing object, and RSSs of all involved radio links are measured. The sample mean of all unaffected RSS average values is defined as the average RSS. In real-time localization scenario, the receiver measures the RSS value, induced by shadowing loss, and calculates its numerical difference from the average RSS of the initial empty environment. The model accounts for link shadowing as a linear combination of the signal attenuation. Different attenuation models presented in the literature are based on spatial impact model of the signal as well as the signal impact on the link. Wilson et al.[79] [55] modified the spatial impact model and developed an ellipse-based geometrical model with nodes coinciding with the foci. In this model, the RSS is either inversely proportional to the square root of the length of the radio link for objects inside the ellipsoid or set as zero otherwise. This model gives quantitative information about the attenuation impact of each link.

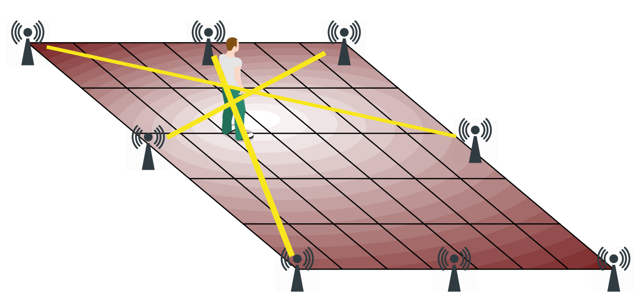

Fig. 8. Target attenuates the links result in variation of RSS[79][55]

Wilson et al.[79] proposed a shadowing based outdoor localization model for object detection. In this model, the RF sensor network monitors the attenuation of the links due to object movement and localize or track the target object. This system calibrates the RSS in static condition devoid of humans or target object, and uses that information to calculate the RSS difference in real-time monitoring. Moroever, the environmental noise is modelled based on Gaussian Mixture Model (GMM), which is a probabilistic model well known for reducing the localization error. To track the moving object, the paper implements the well-established regularization technique. Further, the authors proved that the shadowing model is capable of localizing and tracking single as well as multiple human entities with a significantly lower error value. However, due to all active sensor nodes, this model has the demerit of high power consumption.

2) Channel Diversity: Kaltiokallio et al.[56] improved the shadowing model of RF sensor network using multiple channel communication among sensor nodes. The author proves that the probability of signal shadowing in each link between the sensor nodes is better represented with different RSS measurements from multiple frequency channels. The two-channel selection criteria involved are based on packet reception rate (PRR) and fade level of the link. PRR ensures maximum communication reliability while the fade level concept[109] maximizes the fade level attained within the link. The author also verifies that the channel diversity approach maximizes localization accuracy compared to the single frequency channel approach. The testing is done the indoor scenarios of ground area 70 m^2 and 30 sensor node elements, involving human localization, and the observation was that average errors were less than 0.1m. However, this approach is only applicable to the localization of stationary objects and people. Moreover, the author does not elaborate on the localization principle within the moving object scenario.

3) Ambient Radio Imaging: Energy efficiency is equally significant over localization accuracy in device-free localization systems since sensor nodes are not always connected to power supplies. Energy Saving is a vital requirement for outdoor localization techniques as well as in the indoor scenarios and yet is often neglected. Khaledi et al. [58] focused on the energy efficiency aspect of the device-free localization problem, with localization accuracy in consideration as well. The authors divide the monitoring area into smaller partitions as part of this approach, the partitions with ineffective link RSS variation are switched off. They also suggested two methods for effective link estimation near the target radius based and ellipse based.

In addition, they tested both methods based on energy efficiency and localization accuracy and compared them with shadowing[141] and variance[55] based approaches. Three scenarios were investigated: the office space, indoor area, and a bookstore, for experimentation of the proposal. It was found that an ellipse based approach is better in attaining energy efficiency over other approaches while the radius based approach offers higher accuracy. However, the method is only applicable to single target tracking.

4) Directional Radio Imaging: The majority of the device free localization systems realize omnidirectional antennas for radiation. Wei et al.[85] suggested that the antenna direction can improve the quality of the radio link for better accuracy of localization under device-free conditions. The author implemented a very efficient directional antenna system

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TABLE I. Propagation Model Based Radio Vision Method

Research Work	Model	Deployed Environment	Deployment Range	No.of Sensor Nodes	Measured Physical Quantity	Localization Accuracy	Complexity	Research Findings
[79][55][56]	Shadowing	Outdoor	40 m^2.	28	RSS	0.021-0.036 mean sq. error	$O(n)$,Linearly with Voxel $O(n^2)$, Quadratic with number of sensor node	Localize only one/two person based on radio imaging
[56]	Channel Diversity	Indoor	70m^2	30	RSS	$<$ 0.10 m average localization error	Linearly with voxel $O(n), n = Voxel$	Works in real-time with promising high accuracy
[58]	Ambient Radio Tomography	Indoor	70 m^2	30	RSS	0.172 m (ellipse approach), 0.1544m(radius approach), 0.1693m(basic approach)	$O(n)$ n=voxel but better than RTI due to power efficiency and periodic shut down of sensor	The author considers only the nearby links of moving object by the ellipse or radius model to estimate localization. Hence saving 50-80% of energy.
[85]	Directional Radio Imaging	Indoor	28 m^2	7	RSS of directional links	rms error 0.4340(LoS) and 0.7506(Non LoS)	$O(n^2)$,Quadratic due to number of link measurement	Directional antenna have been used for LoS and non LoS link measurement for better location estimation.
[86]	Exponential Rayleigh Model	Both Indoor and Outdoor	24-36 m^2	four different sets	RSS	0.07-0.21 m. mean error	$O(n^2)$	Exponential Reyleigh RSS model outperform due to mitigation of multipath interference by this model.
[87]	Diffraction Theory	Simulation Study	Short Range	Different Sets Simulated	RSS	0.25-0.4 mean error	$O(n^2)$	Electromagnetic propagation of the link is modelled with diffraction theory.
[88][89][90][91]	Radio Grid	Indoor	Indoor $>$ 16m^2 for each grid	more than 3 for each grid	RSS	Less than 1m	$O(n^2)$ Quadratic complexity due to influential link	Real time tracking system is developed with dividing the tracking field into different area called grid and adjacent area have different communication channel.
[92][93]	Compressive Sensing	Both Indoor and outdoor	variable 144m^2	5	RSS	less than 0.8 m	$O(K.log(N/K))$, K=targets with N sensing nodes	Unifies radio map for different area by using compressive sensing which reduces human effort. This method is applicable for multiple object tracking
[94]	E-HIPA	Indoor	36 m^2	Variable	RSS	0.3-0.4 m	$O(KMN+log(2N))$	Energy efficient multi-target based method using compressive sensing.

called Electronically Switched Directional (ESD) antenna for energy-efficient cost-effective localization. The ESD antenna enables dynamic electronic direction control which has better efficiency than the traditional antenna. Multipath fading is controlled with this directional antenna focusing and collecting signals in the specified direction, thereby improving the link quality. The writers suggested that there are 36 possible combinations of transmitter-receiver pairs for a single radio link. They named these pairs direction-pattern pairs. The pairs that were recognized in this method were compared with existing methods like [79], Variance Radio Tomographic Imaging (VRTI)[55] and Channel Diversity Radio Tomographic Imaging (cdRTI)[56] and validated that it outperforms in terms of localization accuracy for LOS and NLOS conditions.

5) Exponential Rayleigh Model: Guo et al. [86] proposed an RSS based Exponential Rayleigh (ER) model for device-free localization with better performance. The model applies Bayesian inference in estimating state posterior distribution as shown in Figure 9. In this model, the state transitions with respect to time are shown in the state space model, and gives prior state distribution. The constant velocity model represents a moving process of the target. The state posterior distribution is calculated by the particle filter which is a form of Monte Carlo based method. An additional hierarchical clustering process is augmented for multiple target identification in multi-target scenarios. The author applied Hierarchical Agglomerative Clustering (HAC) algorithms for multiple target identification. The major blocks presented in the Exponential Rayleigh (ER) model is given as follows.

- Motion Model: Movement of an object can be modeled as a physical process. Tracking human activity is implemented with a human movement model which is considered as a first-order Markov process. This leads to the Markov process model predicting the next state of the system based on its previous states. Here, the current state of the object motion can thus be predicted from the last state. ER model uses the various state-space models to create object motion.

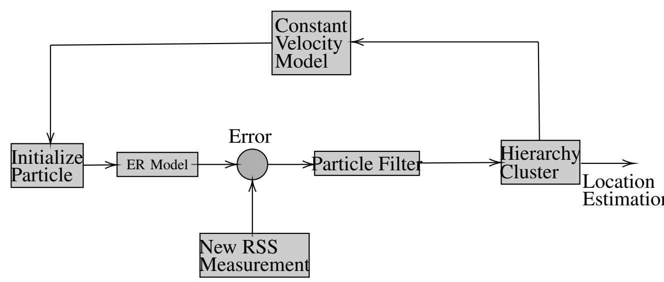

Fig. 9. Device Free Localization with ER Model[86]

- Particle Filtering: In non-Gaussian and nonlinear systems the Monte Carlo method [142] is used to extend the filtering as a particle filter. To achieve an optimal solution, state distribution is expressed using random samples called particles. Particle degeneracy, however, turns out to be a prominent issue, which is then solved with re-sampling methods. In the ER model, Sampling Importance Re-sampling (SIR) particle filter is used for device-free object localization.
- Hierarchical Clustering: Hierarchical clustering is used for multiple object localization. The HAC algorithm [143] is a promising clustering method. In this method, each particle is initially supposed to be independent and after each iteration, clusters are merged under linkage rules and terminated when cluster number equates to the targets. The center of these clusters gives the target state information.
- Multiple Particle Filter: Closas et al. [144] proposed the

Multiple Particle filter for performance improvement in high dimensional targets. The tracking performance is improved in comparison to the standard particle filter.

6) Diffraction Theory: Rampa et al. [87] proposed a diffraction theory based tractable model for moving object localization. The paper depicted the perturbations of electromagnetic signals caused by moving objects near transmitting or receiving sensors. Object size, position and orientation information is estimated by the exploitation of received signal strength measured from multiple radio links.

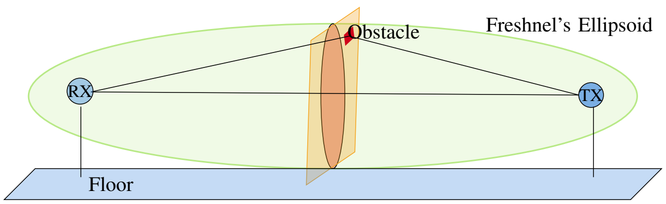

Fig. 10. Device Free Localization with Diffraction Theory[87]

The suggested model is shown in Figure 10. The target object is orthogonally placed in the line-of-sight segment connecting transmitter and receiver. The target is also assumed to be a perfectly electromagnetic absorbing rectangular 2D surface as shown in Figure 10. Location of the link is set above the floor, without the wall and ceiling. The Fresnel's ellipsoid [145] is drawn without any contact with other parts except the target. Ground reflections are ignored in this model. In 2D horizontal space, the target barycentre is located with off-axis displacement. Target objects can move or rotate in any direction along LOS (Line-of-Sight).

Based on this diffraction theory, an ad-hoc model has been developed to describe the fluctuation of radio signals caused by the presence of objects between transmitter and receiver. A lower bound metric, which is also known as the Cramer Rao Lower Bound (CRLB), is applied for estimating the variance. The efficiency of the estimator is measured based on the lowest possible mean square error. Further, Rampa et al. validated the above estimator model, which predicts localization accuracy, in a experimental setup that included different indoor and outdoor conditions [146].

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7) Radio Grid: Zhang et al. [147] proposed the radio grid based device-free localization. This paper explains how the authors had deployed a radio grid in the ceiling and observed the link that was influenced the most by the object. The author reported that the highest RSS fluctuation is along the line of link direction as well as the line perpendicular to it. They then developed a signal dynamics model based on the midpoint, intersection point, and best cover respectively. Experimentation was performed on the model with a 4 x 4 sensor grid in an indoor scenario of floor area 108 m^2, with the single object localization error of 0.7m and 1.8m for two objects which he further improved by dynamic clustering [148][88]. Sen et al. [149] proposed another approach for implementing Radio grid-based method using CSI signal fingerprinting. Due to the high resolution of CSI based methods, it applies to human localization and activity detection. Furthermore, it has been enhanced by research initiatives like breathing detection [150] [151] [152] [153] and occupancy detection[154] using efficient feature extraction from the CSI signal. Depatla et al. [155] further extended a statistical model from RSS to develop a people counting system in an area and also claimed its applicability with CSI model of the signal. Recently Wang et al. [156] had developed a CARM model to characterize human speed using CSI sub-carrier amplitude and former activity model which helps to localize humans based on eight different activities, with accuracy levels peaking at over 80%. Further, this model is improved by the Localization information with Fine-grained Subcarrier (LiFS)[90] model too, using LOS shadowing. LiFS model divides the surrounding link into three zones: LOS, NLOS and First Fresnel Zone (FFZ) which improves the performances of all previous models. It was also capable of localizing human beings without training and less than 0.5meter median error. Pu et al. [157] designed a prototype using software radios for gesture recognition in indoor scenarios. This method can classify nine gestures with an astonishing 94% accuracy by exploiting Doppler shifts. Further, Xing et al. [158] developed another device-free method of human motion detection using Doppler shift and localization principles, by measuring AoA data from directional antennas. Moreover, CSI based device free method is still evolving compared to its active localization counterpart [159][160][161]. Recently SpotFi [162] reported being more accurate than all prior methods with 40cm error using only commodity WiFi devices.

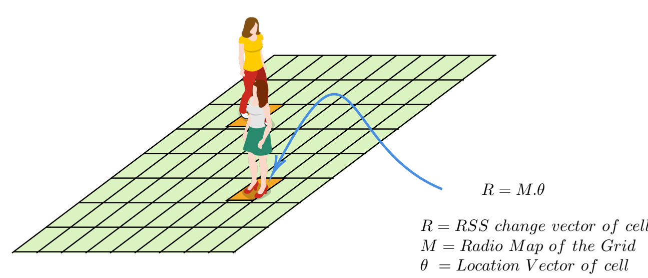

Fig. 11. Compressive Sensing: The real-time RSS of the cell is collected to form RSS vector(shown by coloured cell) and applying compressive sensing theory to localize the target[92][93].

8) Compressive Sensing: Multiple object localization and counting are also possible with Compressive Sensing [92][93] technology. To achieve high localization accuracy, researchers have proposed a dense deployment scheme of sensor nodes. However, Wang et al. [92] showed that high localization is achieved in sparse deployment scenarios also through Compressive sensing approach. Modern device free approaches adopt RSS based measurements since they do not require additional hardware installations for WSN. RSS interference of the link is an important measure for this type of localization approach. Wang et al. [92] considered target location as a sparse signal and reconstructed it using a Compressive sensing approach. This choice of technique was made due to its advantage in sparse recovery. Furthermore, it was mathematically proven that the necessary Restricted Isometry Property (RIP) satisfied for its applicability in the device free localization problem context. They proved that the product of sensing matrix and location vector obeys RIP with high probability as shown in Figure 11. In contrast to existing grid size design for low localization error, the author conducted the Compressive analysis on the appropriate choice of the grid size. Moreover, they validated this approach in localization as well as target counting in large-scale scenarios.

9) E-HIPA(Energy Efficient High Precision Adaptive) Model: Wang et al. [94] developed E-HIPA model of multiple object localization exploiting properties of Compressive Sensing (CS) theory. The author divides the localization problem into two subproblems. The author first formulates device-free localization as a sparse recovery problem by establishing the sensing matrix which satisfies RIP. They then designed a recovery algorithm which adapts to the unknown number of targets. Hence, much of the practical localization problem can be formulated as a CS problem and be solved for a number of practical scenarios. This approach exploits radio signal properties such that when a radio signal propagates the monitoring area, it is diffracted, scattered, absorbed or reflected by the target object. The distorted RSS measurement varies when the target object is in different locations [55][88][163][70].

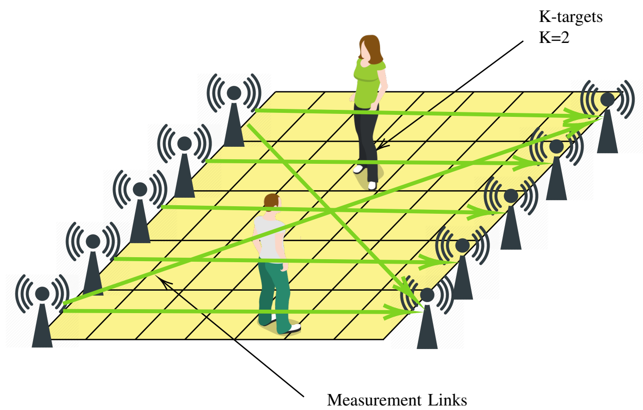

Fig. 12. E-HIPA: This method uses compressive sensing for sparse recovery with reduced link measurement and energy efficiency[94].

The author experimented E-HIPA in the setup as shown in Figure 12. The deployed area is a regular rectangular region with all transceivers positioned at a single hop range. For irregular or vast monitoring areas where the transceivers are not placed in one hop distance, a modified approach is to be followed. First, the big area is divided into smaller subareas. E-HIPA uses additional small rectangular subareas for boundaries of the irregular area to be covered. Finally, E-HIPA estimates the target location simultaneously in each subarea.

B. Summary and Insight of Propagation Model

A localizing object exploiting the radio links of the deployed region is a compelling challenge. It may be overcome with different propagation modelling approaches like shadowing, channel diversity, directional link pair, Rayleigh model, etc. The numerous approaches proposed by authors have been verified in indoor and outdoor scenarios.

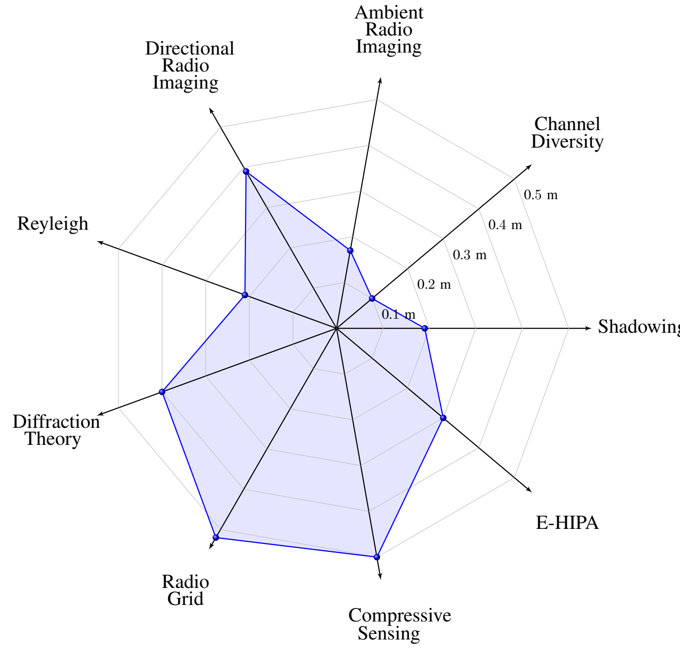

Fig. 13. Comparative localization error analysis of Propagation Model.

In Table I an extensive comparison of the protocols are presented. A comparative plot of localization accuracy is depicted in Figure 13. It is observed that The channel diversity method gives the lowest error of 0.1m. In addition, shadowing scheme, energy efficient model, and Rayleigh framework generate localization errors below 0.2m. Hence, these methods can further be modified to improve localization error measures in the device-free context.

V. Statistical Model Based Device Free Localization

The vital foundation of various localization systems is the capability of the system for proper navigation signal acquisition. In DFL installations, the target localization is calculated with RSS or CSI data from the link, followed by various estimation processes. Information unification and fusion are the core technologies behind various statistical methods. The following subsection presents the different statistical model based DFL systems and a critical analysis of the existing DFL systems are presented in Table.II.

A. Statistical Models

1) Sequence Montecarlo: In DFL systems, wireless link modeling is essential for location estimation. Zheng et al. [95] developed a movement detection method and implemented it in WSN. The communication link is modeled on a Gaussian Mixture Model distribution for RSS measurements. A foreground detection method was applied followed by Sequential Monte Carlo (SMC) algorithm. The probability of affected

TABLE II. Statistical Estimation Model Based Radio Vision Method

Research Work	Model	Deployed Environment	Deployment Range	No.of Sensor Nodes	Measured Physical Quantity	Localization Accuracy	Complexity	Research Findings
[95]	Sequence Monte-carlo	Indoor	16 m^2	24	RSS	0.2 m rms error	$O(n^2)$ Quadratic in sensor node	Stationary and moving objects are located in both LoS and non LoS scenarios.
[164][55][96]	Variance	Indoor	70 m^2.	34	RSS	0.45-1.03 m mean error.	$O(n^3)$,Cubic depends upon link	Capable of localizing the object behind the wall.
[98]	Histogram Distance	Indoor	16m^2.	16	RSS	0.7m rms error	$O(n^2)$, Quadratic depens on link	RSS from static link is measured and histogram difference of RSS is the metric used for quantifying the change of RSS difference. It works in lower sensor node density.
[96]	Subspace Variance	Indoor	70 m^2	34	RSS	0.10 m mean error	$O(n^3)$	This improved version of variance method proposed to improve accuracy by 41%.
[99]	Kernel Distance	Indoor	60 m^2	34	RSS	0.7m rms error	$O(n)$	The author proposes radius and ellipse based approaches which are 50-89% energy efficient.
[100]	Fade Level Model	Indoor	70	34	RSS	0.30 m mean error	$O(n^2)$,Quadratic in terms of sensor node	Measures the field in either constructive or destructive interference settings and predict the location with a probabilistic model
[101]	Three State RSS	Indoor	48 m^2	3 different setup	RSS	0.07-0.46 m	$O(n^2)$,Quadratic with repect to sensor node	The channel is modelled with three different states of electronic noise, reflection and shadowing. Hidden Markov and Particle filter is used to estimate and track the object.
[102]	Hierarchical RSS	Both indoor and outdoor	Different exp. setup taken	26	RSS	0.118-0.293m	$O(n^2)$	Refine the RSS variations granularity of the links and enhance the RSS from shadow fading
[70]	Nuzzer	Indoor	55.7m x38.8m	Grid of Sensors with spacing 2m	Changes in RSS	less than 1.82m	$O(n^2)$	This is a variance based RSS estimator which is applicable for coarse gain localization of the object.
[103][104][60]	Bayesian Model	Indoor and Outdoor	different indoor scenarios	35	RSS	0.1-0.2 m.	$O(n^2)$,Quadratic in terms of node	RSS measurement is probabilistic modelled and used in different filtering techniques for the optimized link
[105][106][107][108]	Particle Filter	Indoor	8m x8m	Variable with different expt	RSS	0.2-0.7 m (single target 0.2m)	$O(NM^3)$,Linear in N target and cubic in M sensors	Capable of Multi-target tracking with good accuracy
[109]	Skew Laplace Model	Indoor	10m x10m	Variable	RSS	0.58 m and 0.91m mean error in two expt.	High or Polynomial time	Single and multiple objects can be tracked with this fade level model of RSS. Author defined the fade level as a Skew Laplacian distribution and estimated the location with a particle filter.
[110][111]	SCPL	Indoor	150 m^2 and 400 m^2(two expt)	23 and 20 (two expt)	RSS Change	less than 1.3 m. mean error	Factorial Computational Complexity	Sequential Counting and Parallel Localization method presents 86% correct counting and multiple localization results with good accuracy.

link is modeled as a classification problem in foreground detection, then estimated from RSS measurement and taken as a mean value. The SMC is applicable for the both non-linear and non-Gaussian scenario to provide a good solution. System performance is evaluated by the author in a radio network comprising of 24 RF sensor nodes in a building. They proved that the link structure could be used to estimate the individual location. It is inferred from the experiment that without any offline training this particular method achieved an impressive 0.2m root mean squared localization error in the dynamic environment. Not to mention how effectively this method applies to LOS and Non-LOS scenarios.

2) Variance Model: The propagation radio model based approach relies on the initial calibration of the environment without the presence of the object. Changes in the environment lead to error in localization and the resultant requirement of recalibration. Wilson et al. [55] proposed a variance based DFL system. their approach, the region for localization is divided into the grid of physical spaces called the voxel. On the other hand, a vector of RSS variance [164] represents the links' shadowing area, which can be used to determine the occurrence of the target in a physical space. This method does not require calibration of the empty environment before object localization and encompasses the variations in the environment. This work demonstrates the application of the normalized ellipse weight model for link shadowing or attenuation. The moving target is localized by Kalman filtering in the voxel space with regularization technique [79]. The author verified this method by conducting an experiment taking 34 sensors in indoor home scenarios and recorded a localization error of 1.03m. Further, they reduced the delay induced by the Kalman filter and improved this accuracy beyond by arriving at a better localization error score of 0.45m. There is however a downside that the method is not power efficient, since all the RF sensors are always active, and also fail to localize static objects on account of the lack of RSS variations.

3) Histogram Distance: A traditional DFL system requires pre-calibration of devices in the empty environment. This limitation is overcome by Zhao et al. [98] with a Histogram Distance based DFL system. It is a system capable of localizing both stationary and mobile targets without pre-calibration. The histogram difference metric computed here is availed to quantify the RSS change, which further estimates the location. This method works well in lower node densities. The author had also classified short-term and long-term histograms. When an object is located near the line-of-sight (LOS) of a link, the RSS histogram of the link significantly deviates from the calibrated RSS histogram for a short time period. The deviated histogram is called a short-term histogram, and the previously calibrated RSS histogram is called long-term histogram. These two types of histograms are measured based on a metric and the difference between these two is determined by Kullback-Leiber divergence [165]. The metric definition and its calculation is computationally complex, but is simplified by applying kernel-based approaches. The location is then estimated from this histogram using different metrics. The logic is also enhanced further by Zhao et al. [99] with histogram difference and online calibration approaches. The proposed model was experimentally verified with 16 nodes deployed in a 16 m^2 area achieving a notable 0.7m root-mean-squared localization error, which is better than all the Variance Based DFL models. [79][55].

4) Subspace Variance: There is always a variation in link RSS value whenever an object interacts with the RF links of an RF sensor network. These variations in RSS help in the estimation of an object or target human. However, the unwanted variations of RSS due to external phenomena like wind, vibrating machinery, and other natural influences cause RSS variations and thereby degrade the DFL system performance. Zhao et al. [96] proposed and extensively verified a subspace decomposition method to reduce the unwanted RSS variations due to natural interference. These unwanted RSS variations in the measurements collected are called intrinsic measurements. A majority of intrinsic measurements in RSS are represented in the lower dimensional space as Principal Components by Subspace decomposition method. The components of the measured RSS are also decomposed into intrinsic and extrinsic sub-spaces respectively. Further, the subspace decomposition method is used to reduce intrinsic RSS. The algorithm was verified through experimental scenarios of 70 m^2 with 34 sensor nodes and achieved 0.1m mean localization error. This method reduces root-mean-squared localization error by 41%.

5) Kernel Distance Based DFL Model: In histogram distance[98] based DFL system there is an issue pertaining to the calculation of histogram distance with low complexity and that makes the system computationally complex. Zhao et al. [99] further modified the system with Kernel distance approach and successfully located static and dynamic objects in LoS scenario as well as non-LoS scenarios. This method quantifies the histogram difference between two histograms of RSS measurement. The author critically compared the histograms with different metrics such as Kullback-Leibler Divergence (KLD) with the kernel distance and found that kernel-based approach beats other methods. They validated the kernel-based approach by conducting five experiments with the dataset from Wilson et al. [109] experiments. Finally, a comparison was made between the kernel method and other DFL methods [55] [96][95] and the inference was that it is only applicable in the real-time method for localization in LoS and Non-LoS scenarios without training.

6) Fade Level Model: In RF sensor networks, the RSS changes considerably for each communication link due to the spatial impact of the object or the moving individual. These spatial impacts should be modeled intelligently for better localization accuracy in DFL systems. Kaltiokallio et al. [100] improved the fade level model as described by Wilson et al. [109]. Fade level model records constructive or destructive interferences in the link and further exploits this link measurement in the network for localization. The difference in radio propagation and mean RSS of a link for a specific channel is called the fade level of the link for a channel. Based on the RSS change in a special impact area, the probability of the presence of the object is calculated. Further, the author used regularized least square and Kalman filters to track the motion of the object. This model has been verified with three experiments in 70 m^2 open-indoor, 58 m^2 single bedroom and 70 m^2 lounge room scenario and the results are compared with the channel diversity [56] based DFL model. This technique can also localize a human in the three scenarios with high accuracy. In the open-indoor scenario, the fade level model reported 0.17m. average localization error compared to channel diversity model which gives 0.25m. average error. The average localization and tracking accuracy of fade level mode for the single bedroom scenario are 0.26m and 0.23m average errors respectively which is significantly better than channel diversity model achieving errors of 0.31m and 0.24m respectively. In the lounge scenario, the fade level model reported 0.30m localization error which improves the 0.72m reported by the channel diversity model. The fade level model may thus be inferred to work better with fewer sensor nodes compared to channel diversity. It was also noticed that upon removing eight nodes the accuracy in the fade level model was reduced by 27% whereas when nine nodes being removed caused the accuracy to drop further to 56% in channel diversity model.

7) Three State RSS: Kaltiokallio et al. [101] proposed a three-state RSS model where the measurements are dictated by electronic noise, reflection or shadowing depending upon the object to be localized or tracked. Based on this model, the statistical and spatial model for different states are derived as shown in Figure 14. A monitoring application for the links is developed to estimate the state of the target object and temporal state of the propagation model. The author claimed that this model gives higher localization accuracy than the rest of the empirical models even if the sensing region of the sensor nodes are increased. This three-state RSS model is the modification of conventional time-varying two-state channel model with an extra state included. This model can estimate human location by human-induced temporal fading in the two states. In one state the human-induced effect changes the amplitude of the received signal by shadowing and in another state a new multipath component is created by reflection. The model is successfully implemented in a cluttered indoor scenario. An assumption of a coherent receiver architecture is made since they allow straightforward determination of the relationship between changes in RSS with temporal variation. The receiver is assumed to be synchronized to the LOS component [56] and changes in RSS measurement depends on LOS signal. The objective was to capture tiny changes in the channel that is observable for all frequencies. There was also validation on this model by an indoor experiment with 48 m^2 area obtaining localization error between 0.07m to 0.46m.

8) Hierarchical RSS: The significant challenges faced in the context of RF sensor networks for device-free localization is the decrease in sensitivity to shadow fading and performance degradation in cluttered environments. To address this problem Luo et al. [102] proposed a hierarchical RSS model for enhancement of RSS variation sensitivity to shadow fading. The author combines the Exponential-Rayleigh (ER) and Diffraction model to parametrize both targets-generated multipath interference and diffraction fading interference. RSS variations concerning fade levels characterize these model coefficients. The illustration of the hierarchical structure is

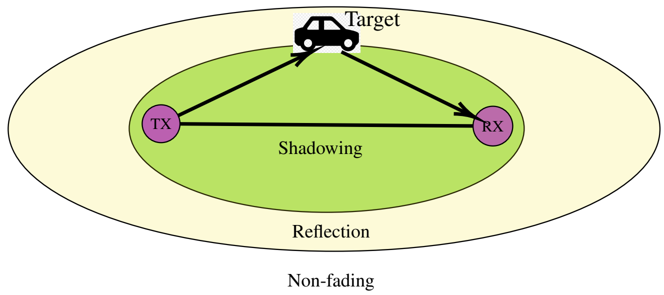

Fig. 14. Three State RSS Model[101]

shown in Figure 16. In comparison to other models like the elliptical model or the ER model, this hierarchical approach represents the fading effect with more degrees of freedom. A mathematical approximation of the hierarchical model to diffraction-based model and ER-model in different scenarios is developed. This model also incorporates the diffraction within LoS path bounds and reflection outside LoS path. Hence, the target induced changes in the RSS values are captured in this model.

9) Nuzzer: A probabilistic model based DFL system called Nuzzer is developed by Seifeldin et al. [70]. The Nuzzer system has two operational phases; the offline phase and the online phase. During the offline phase, a passive radio map is built. The map is similar to an active radio map used for device-based active localization systems [166][167][168]. In the active radio map, the user collects RSS samples in a mapped location of the network from all the access point using a device. However, in the passive radio map, the user does not carry any device; only the target's effect on RSS data stream recorded. The passive radio map data contains histogram per raw data stream as compared to histogram per access point in the active map. Whereas in the online phase, the target object is localized with each zone based on RSS from each data stream. Two modes were proposed by the author for online phase; discrete space estimator and continuous space estimator. The discrete space estimator outputs calibrated locations from the RSS vector of different streams that have maximum probability. After the discrete space estimator gives a calibrated location, the continuous space estimator processes a more accurate estimate of the target object. The authors experimented with six data stream and concluded that the Nuzzer system gives a good performance, especially in the context of the non-line-of-sight device-free localization system. This system covered high multipath and a large area with an accuracy of 1.82 meters in the first experiment and 0.85 meters in the second experiment.

10) Bayesian Model: The DFL system is aptly categorized into model-based approaches and training based approaches. A model-based approach follows either linear techniques or statistical estimation rules. In a Bayesian DFL approach, first the RSS measurement model is developed. Subsequently, the Bayesian filter is used to estimate the state of the target. The different Bayesian-based measurement models include elliptical model [169], exponential model [170] [171] [86], diffraction model [103] [172] and three-state model [101]. The complexity of the elliptical model is the lowest and the three-state model is the highest. These models are all nonlinear in properties, so nonlinear filtering is to be applied for tracking the targets. Different modes of Bayesian model [103][104][60] are present in the literature. Commonly, in DFL systems the huge quantity of RSS data needs to be processed for location estimation and these may encounter data transmission disasters. Wang et al. [104] proposed a binary mode of operation of RF sensor networks to overcome this transmission disaster. In this approach, the RF sensor detects only the link states, interfered or otherwise, as shown in Figure 15. This link-state information is further processed to estimate target location. Different indoor scenarios have been experimented and average localization errors are from 0.1m to 0.2m.

11) Particle Filter: A particle filter is an estimation approach for solving the localization problem. Markov chain based particle filter is proposed for multiple object tracking [106] [107]. The RSS value can be expressed in three main terms; average RSS - when no target present, attenuation of the link - when target present, and Gaussian noise affected RSS measurement. They estimate target motion based on the Markovian dynamic model. The author assumed multiple targets move independently of each other. The authors experimentally validated the model with 24 wireless sensor nodes in a 49 m^2 area. The tracking accuracy in a two-target case is 0.6m and for four-target is 2.5m. This method is further modified by Nannuru et al. by joint target posterior density model called Probability Hypothesis Density (PHD) [108]. It's a function of single-target state space. This value is high in regions where the location of multi-target is more. The integral of this PHD over target state space gives the expected number of targets. The robustness of the measurement models is analyzed by considering the standard deviation of two different noise values. The author finally concluded the mean square error tracking accuracy of 0.3m, 0.7m and 0.8m for single, two and three objects respectively.

12) Skew Laplace Model: The RSS measurement is modelled with a continuous probability distribution. The distributions are a different form of Laplace distribution. Wilson et al. [109] developed a statistical inversion method of DFL system using Skew-Laplace model. In this model, RSS attenuation is modeled using Skew-Laplace distribution derived from training based parameter estimation. The temporal fading in the static link enables statistical inversion method in RSS model. The author suggested two functions of current position and fade level. The target movement depends upon the steady state as well as narrowband and temporal fading. Experimental confirmation was obtained that a fade level quantifies the presence of the target in this system. When a target is present, a high variance of RSS is observed, and destructive interference is observed in the absence of the target. Verification was also made that this model with 100 m^2 area using a different set of sensor nodes based on IEEE 802.15.4 standard. In this experiment, they have located two stationary and moving targets, even though the external building wall with a mean localization error is 0.58m and 0.91m for each experiment respectively.

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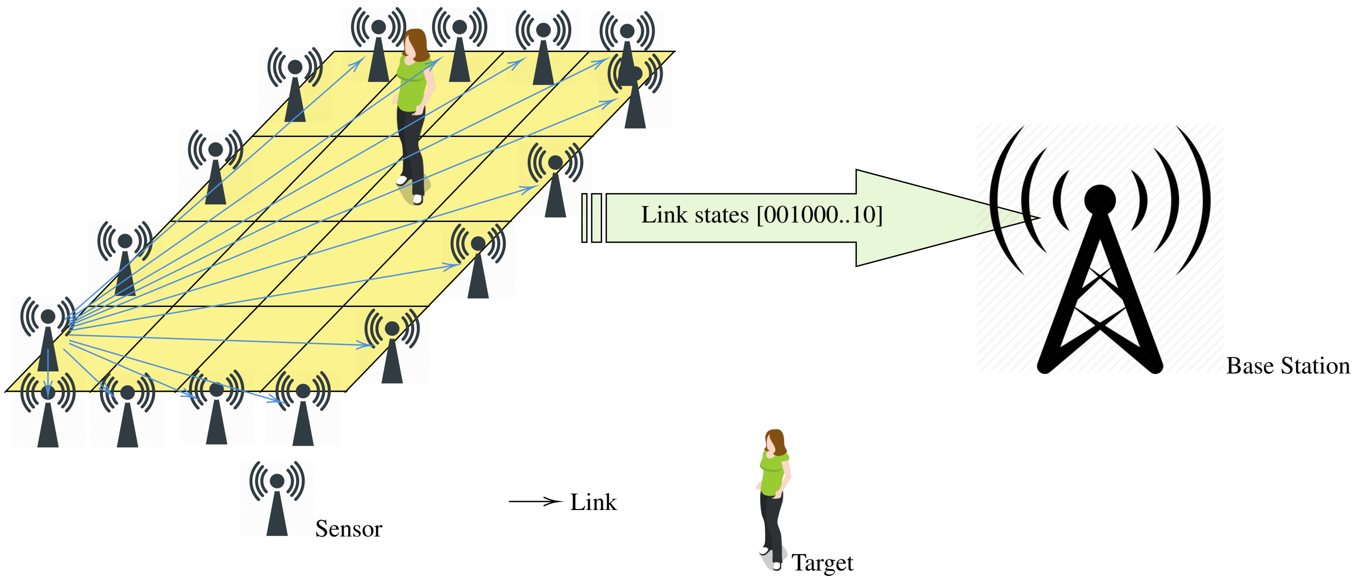

Fig. 15. Binary Mode Bayesian DFL system

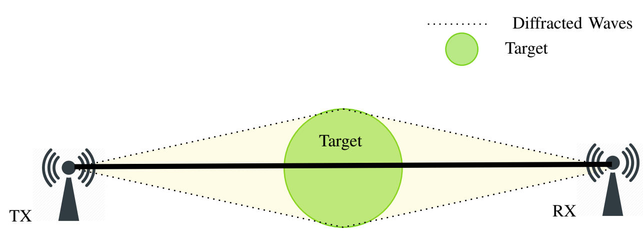

Fig. 16. Hierarchical RSS Model based DFL system[102]

13) Sequential Counting Parallel Localization(SCPL): Xu et al.[110] suggested a DFL system based on RF sensor network called Sequential Counting Parallel Localization (SCPL). This method follows localization and counting stages with the latter following a sequential cancellation method. In this method, first the room is checked for the presence of the target. If a target is found then the location of the target is checked and its impact on the radio link is subtracted. In multiple individual scenarios, the specific localization coefficient of the individual is multiplied by the individual's impact on the link before subtraction. If the number of individuals is known, then the localization phase is initiated with parallel tracking of multiple individuals. Additionally, in this method the computation is done by partitioning the entire area into smaller cells. The author modeled human trajectory as the Conditional Random Field (CRF). The author validated this model with two experiments; one in 150 m^2 cluttered office environment and other 400 m^2 open floor plan. It was conducted with 20-22 sensor nodes operated in the 909.1 MHz frequency band. The first experimental results had a counting accuracy of 84% across all cases while the second experiment showed 100% accuracy for single target but achieved 82%, 80%, and 83% for four, three and two targets respectively. Total counting accuracy reported in this method is 86%. Hence from the experiment, it can be concluded that SCPL method leads to proper counting and localization results for limited targets, but failed for more significant numbers of targets.

B. Summary and Insight

Different statistical models-based DFL systems have been critically analyzed and presented in Table II. Wide varieties of deployment ranges and accuracy are analyzed and research findings are compared. A localization accuracy based spider plot is formed to compare the existing localization techniques and categorized the algorithms in different accuracy zones. Bayesian and Subspace variance-based approaches are found to be the most accurate DFL systems with localization error below 0.1m. The Nuzzer and SCPL methods are the lowest accuracy methods though they support multi-object tracking. The comparative plot is given in Figure 18.

VI. Training Based Device Free Localization

A. Training Based Methods

The training based DFL systems use a database of training measurements and estimate the target location by comparing a measurement taken during online phase with the training measurement database. A comparative critical analysis of training based DFL system is presented in Table III. The comparative research finding and localization error in the different scenarios are plotted and explained.

1) Extreme Learning Machine: The RF-based DFL system measures the RSS and fuses these measured values to estimate the location. Zhang et al. [112] proposed an extreme learning machine (ELM) [173] based DFL approach to enhance efficiency and localization accuracy. In this paper, the proposed work is a parameterized geometrical representation of the affected link. This representation consists of geometrical intercepts and differential RSS measurement. The features from the affected links are obtained by Parameterized Geometrical Feature Extraction (PGFE) method and fed into the input of ELM. PGFE-ELM for DFL is trained and tested with

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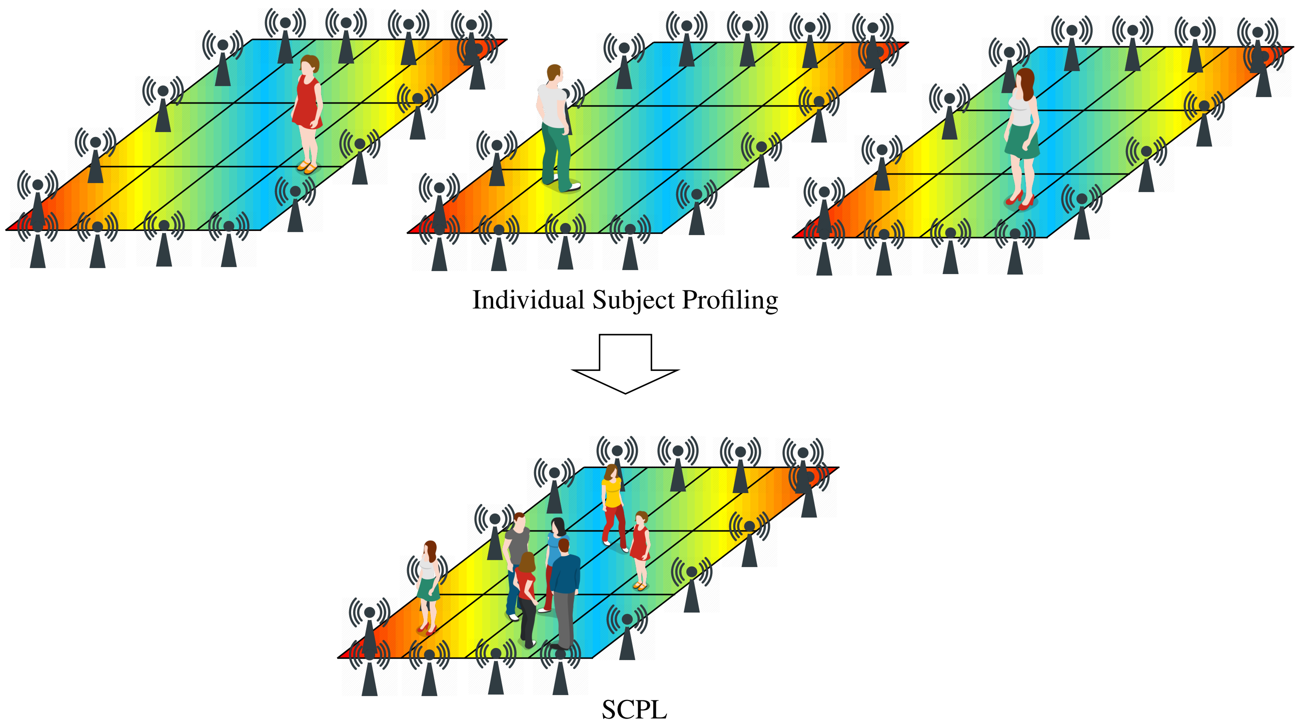

Fig. 17. Sequential Counting Parallel Localization(SCPL):First the profiling data is collected for single target followed by successive cancellation based algorithm to determine the number of target and its location.[110][111]

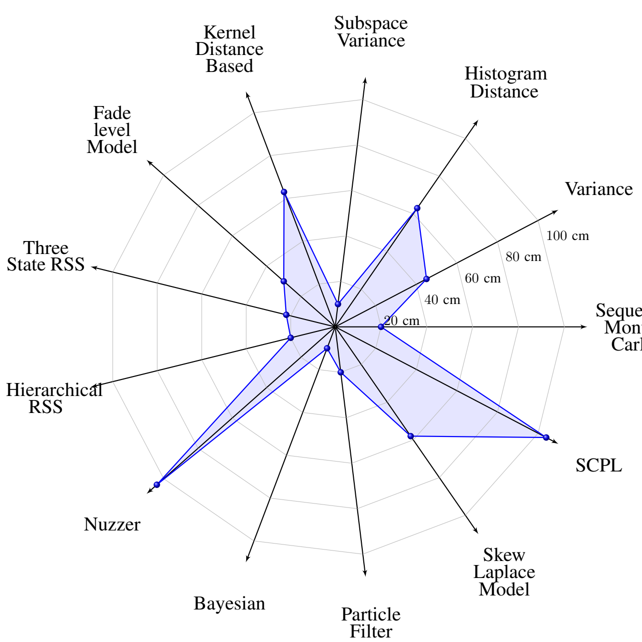

Fig. 18. Comparative localization error analysis of Statistical DFL Models.

the created ELM as shown in Figure 20. The method has proven to be robust to the uncertain combination of wireless links which is frequent due to uncertain wireless propagation. Experiments on this method had proved it to be superior to the Weighted K-Nearest Neighbor (WKNN), Back Propagation Neural Network (BPNN), Support Vector Machine (SVM), as well as the popular Radio Tomographic Imaging (RTI) DFL approach. Back-Propagation Neural Network (BPNN) and Support Vector Machine (SVM) [174] get trapped in the local minimum and had a time-consuming training phase. This method is much faster than traditional machine learning algorithms [175][176][177]. Due to classic advantages like unified learning, binary classification and multiclass classification it is applicable to many DFL based systems like face recognition [178][179], industrial production [180][181], human physical activity recognition [182][183], landmark recognition [184][185] and leukocyte image segmentation [186], etc.

2) Channel Selection with Regression: The DFL systems are prone to environmental changes and therefore need recalibration to sustain the system accuracy. Lei et al. [113] developed a system based on enhanced channel selection and logistic regression to improve localization accuracy in this changing environment. The author proposed a frequency channel selection method that select two correlated channels with higher Pearson correlation coefficient for RSS training and testing procedure for the robust environment. Logistic re-

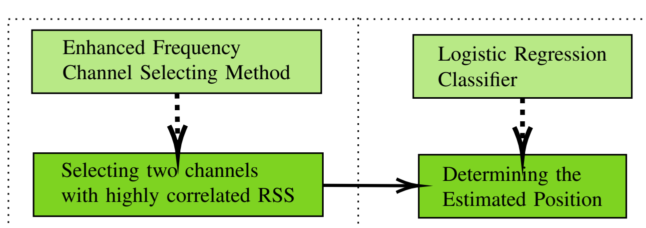

Fig. 19. Channel Selection with Regression Method[113]

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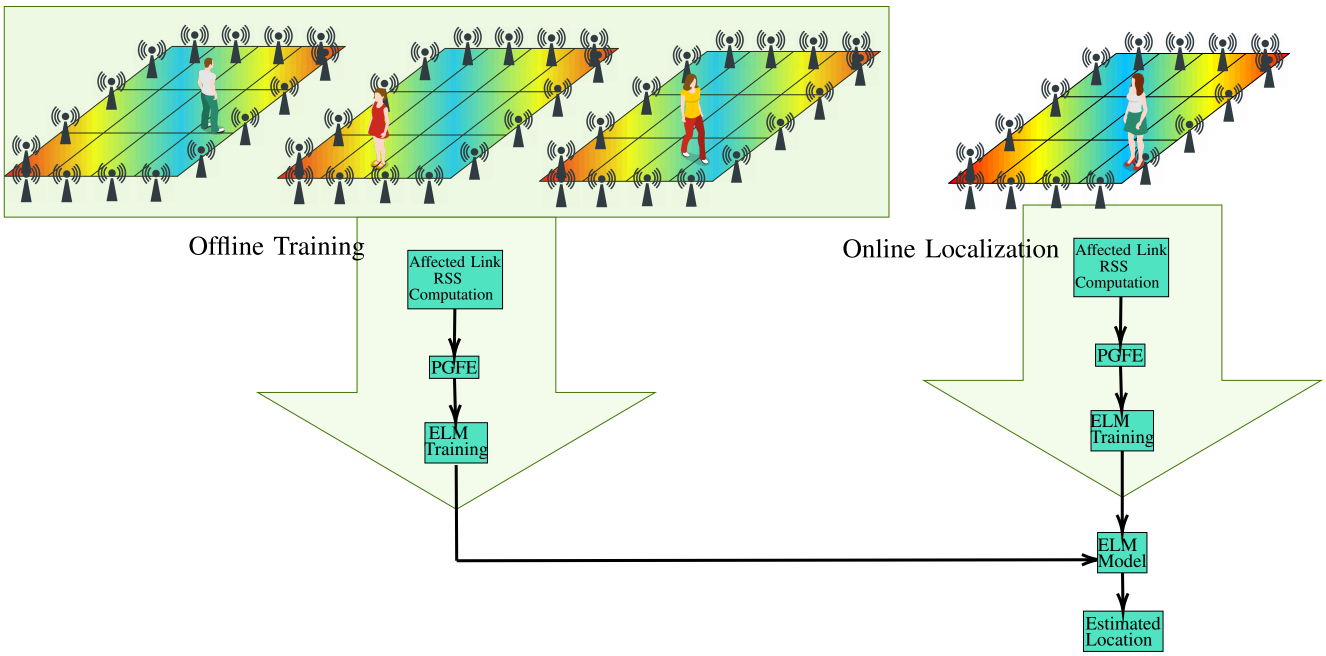

Fig. 20. PGFE Extreme Learning Machine Based DFL[112]

gression classifier improves the localization accuracy without database rebuilt in this DFL system. The proposed framework is illustrated in Figure 19 and consists of two steps - first, the selection of highly correlated RSS channel pair, and then applying a logistic regression classifier. The highly correlated channel selection step used training and testing procedures [187][188] for two correlated channels, followed by logistic regression for location estimation. The author experimentally verified this method is giving lowest localization error than k-nearest neighbours classifier, linear discriminant analysis classifier, and random forests classifier.

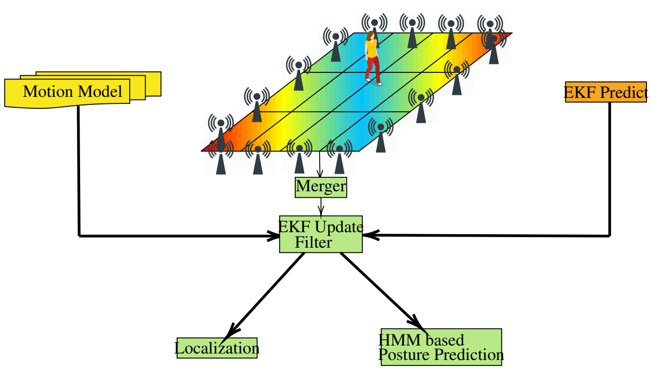

Fig. 21. DFL system of body localization using Markov model[114]

3) Markov Model: Kianoush et al. [114] developed a human body motion sensing and body localization and fall detection method. This method is based on the Hidden Markov Model (HMM) techniques and uses RF signal property obtained from a sensor network placed in a workplace environment as shown in Figure 21. This system monitors RF signals in the 2.4 GHz ISM band and supports machine-to-machine communication functions. Human-induced diffraction and multipath effect are considered for RF signal monitoring and help body localization with RSS footprint analysis and Markov model-based predictor. The system can localize individual position, motion and health-critical posture. This method can further apply to worker safety and protection in industrial applications. The source of information is fused with other sensor information for several monitoring activities. The author verified this method in terms of sensitivity and specificity. Experimental evidence from the model with 14 m^2 area with 12 sensor nodes and achieved 0.198m average localization error.

4) Probabilistic Classification: Xu et al. [115] proposed a linear discriminant analysis (LDA) based DFL system using probabilistic classification (PC). The multipath effect is reduced in this method and recalibration is done on the training data to maintain accuracy in adapting to environmental changes. The proposed system design is shown in Figure 22, it follows a layered sensing paradigm of sensing layer, aggregation layer and analysis layer. The important block

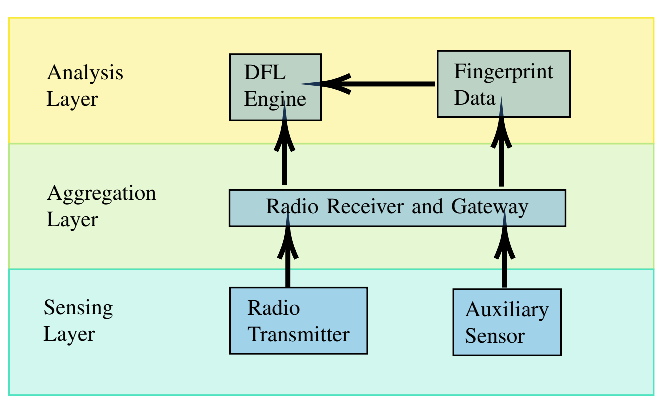

Fig. 22. Probabilistic Classification[115]

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TABLE III. Training Based DFL Systems

Research Work	Approach	Deployed Environment	Deployment Range	No.of Sensor Nodes	Measured Physical Quantity	Localization Accuracy	Complexity	Training/Prediction Delay	Research Findings
[112]	Extreame Learning Machine	Indoor and Outdoor	6m x 6m	16	RSS	0.7-1.40 mean error.	Quadratic	Training 0.01sec, Prediction .001sec	Parameterized geometric representation of affected link is developed and ELM is implemented from the feature extracted from the affected link
[113]	Channel Selection with Regression	Indoor	84 m^2	30	RSS	3.34% average error rate of all expt.	Quadratic	Moderate	Localization accuracy is improved by enhanced frequency channel selection with logistic regression algorithm.
[114]	Markov Model	Industrial Workspace	4m x 4 m	12	RSS	0.198m average error	Linear	High	This method is based on Hidden Markov Model(HMM) which uses Radio Frequency signal property for localization of human in indoor environment.
[115]	Probabilistic Classification	Indoor one bed room appartment with 32 cells	5m x 8m	8 transmitter& 8 receiver	RSS	0.36m average error.	Cubic in training and Quadratic in testing	Moderate	Probabilistic classification based device free localization method is proposed and validated with linear discriminant analysis (LDA) with 97% localization with basic accuracy over 97%.
[116]	iUpdator	Indoor office,library & hall	9m x 12m(office),8m x 11m(Library), 10m x 10m(Hall)	8 WiFi AP	RSS	0.5-1m error	Quadratic	Moderate	Self-augmented Regularized Singular Value Decomposition (RSVD) method is implemented with the properties of the RSS fingerprint database
[117]	Gradient FingerprinTing(GIFT)	Five Story Campus building	8000 m^2	Several WiFi AP	RSS	less than 5.6 m with dynamic wifi signals	Quadratic	Moderate	A novel GradIent FingerprinTing(GIFT) method is proposed which is adaptable with time varying signals and device heterogeneity.
[118]	CSI with SVM	Indoor(lab,room)	7m x 6m(lab), 6m x 6m(room)	2 transmitters and 2 receivers	CSI	1.22m(lab),1.39(room)	Polynomial time	Training and prediction 4msec	Channel State Information(CSI) based localization approach is presented with SVM which shows 97%presence detection precision.
[119]	Machine Vision	Indoor(apartment, office)	67 m^2(office), 58 m^2(apartment)	32(office), 33(apartment)	RSS	0.45m peak error(two targets), 0.46m peak error(three targets), 0.55m peak error(four targets)	High Polynomial time for multiple object tracking	High	Real-time RF sensor network capable of localizing multiple targets is developed with radio tomographic imaging based machine vision method.
[120]	CRF based Markov Model	Indoor	12m X9.5m(test 1), 11mX12.3m(test2)	25	RSS	less than 1.3 m.	Linear time	Prediction delay 1.9 msec	A combination of probabilistic energy minimization with conditional random field with Markov Model is proposed with multi object tracking capability.
[121]	Deep Learning	Indoor	7.2mX 7.2m(lab), 9m X4.5m(apartment)	9	RSS	0.85m(lab) and 0.88m(apartment)	High Polynomial time	High	Device Free Localization and Activity Recognition (DFLAR) method is suggested by the author which uses Deep Learning for establishing relationship between shadowing effect of wireless link with location.
[122]	Dictionary Learning	Indoor	21 x 21 sq. ft.	12	RSS	92.86%	Quadratic	50-60msec prediction delay	Device free localization problem is formulated as an optimization problem. Further the path tracking is improved by tracking neighbourhood rule.

is the PC-DFL engine which streams radio data, combines fingerprint data and runs a localization module to estimate location. The sensing layer constitutes an auxiliary sensor and automatic recalibration module. Validation on this method in a one-bedroom apartment scenario with 32 cells, using 16 sensor nodes. The environment is highly multipath prevalent but still they achieved localization of individual with more than 97% cell estimation accuracy with localization error up to 0.36m. System accuracy is always maintained over 90% even with the reduction of sensor nodes from 16 to 8. Accuracy levels are achieved through standard training methods which can extend the lifetime of training data for a month with estimation accuracy over 90%. The auxiliary sensors in the module automatically recalibrates to improve the localization accuracy as shown in Figure 22.

5) iUpdator: The DFL systems based on fingerprinting approach are popular due to low deployment cost and good accuracy. Chang et al. [116] developed a DFL system called iUpdator using Self-augmented Regularised Singular Value Decomposition (RSVD) augmenting the sparse attributes of the fingerprint database. iUpdator can update the whole RSS fingerprinting database at reference locations. This algorithm can sense the variation in RSS difference and is able to detect the neighbouring wireless link similarity too, which in turn facilitates overcoming short-term RSS variation.

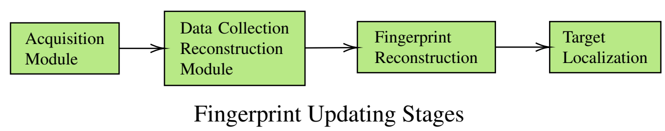

Fig. 23. iUpdator[116]

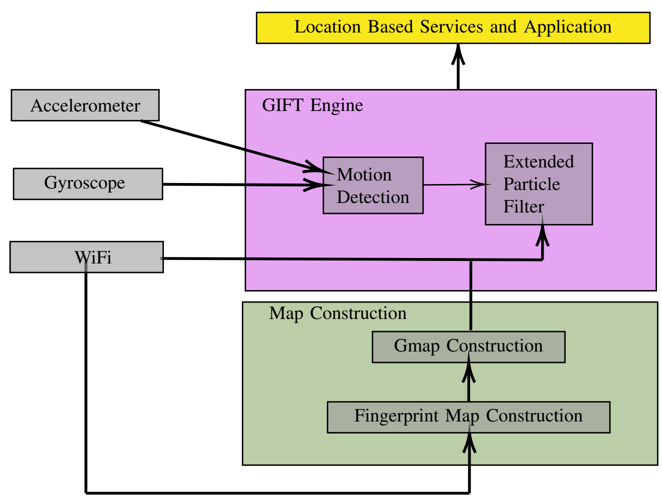

Fig. 24. GIFT module architecture[117]

The iUpdator method consisting of four modules of inherent correction acquisition, reconstruction data collection, fingerprint matrix reconstruction and localization module as shown in Figure 23. In inherent correlation module, iUpdator extracts Maximum Independent Column (MIC) vectors from fingerprint matrix followed by inherent correlation matrix formation. The inherent correlation matrix contains constraints for reconstruction fingerprint matrix. In reconstruction data collection module fresh RSS measurement at the minimum number of reference location are collected to form the refer-

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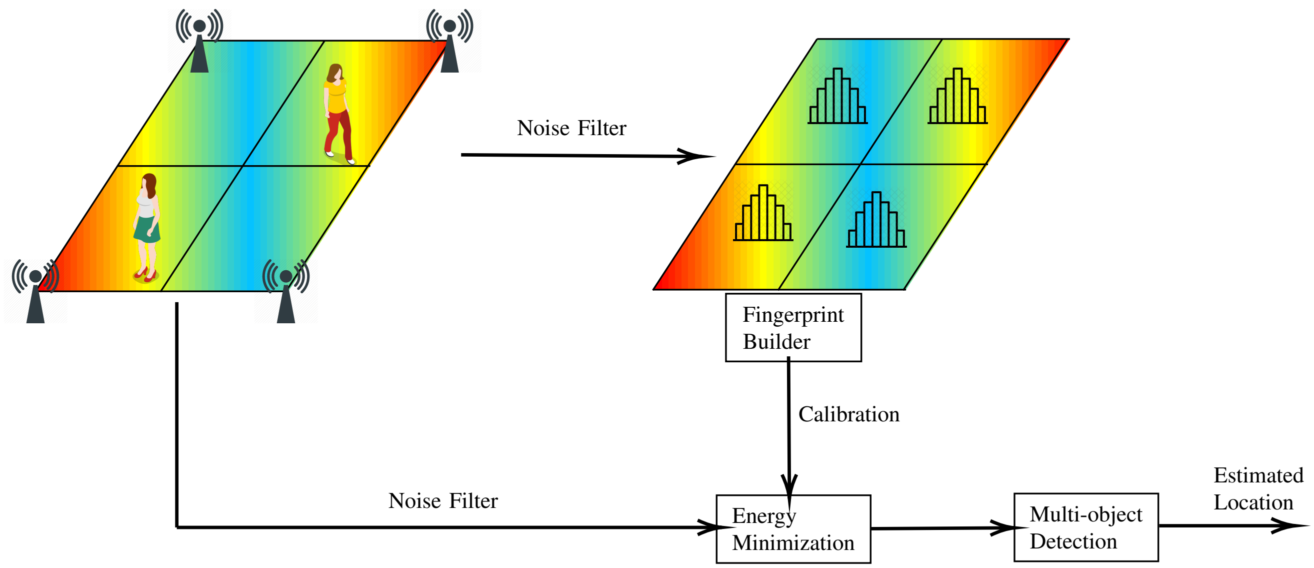

Fig. 25. Conditional Random Field based Markov Model[120]

ence matrix. Besides far away points from direct links are also acquired and referred no-decrease matrix. Fingerprint matrix is constructed with self-augmentation RSVD method from the correlation matrix, reference matrix and no decrease matrix. In localization module, reconstructed fingerprint matrix is exploited with non-linear optimization method to estimate the final location of the object. The author experimented this method in three scenarios of 108 m^2 office, 88 m^2 library and 100 m^2 hall with 8 WiFi access points and obtained 0.5-1m localization accuracy.

6) Gradient Fingerprinting based DFL: The fingerprinting method compares WiFi fingerprint of RSS with the pre-established fingerprint map of a specific location. The fingerprint map of a place changes with the modification in the environment, so there is the need for recalibration of fingerprint map periodically to sustain the accuracy of the DFL system. Also, RSS measurement due to heterogeneous devices supplements error in DFL systems. To overcome these issues, Shu et al. [117] developed a GradIent FingerprinTing (GIFT) technique which gives more stable RSS gradient. In this method, the RSS values are collected and compared to build a gradient-based fingerprint map (Gmap) followed by online Extended Particle Filter (EPF) for target localization. The GIFT is adaptive to RSS change in an environment so does not need further fingerprint map calibration. The GIFT has a map construction module and GIFT engine as shown in Figure 24. First, Gmap is constructed from existing absolute value fingerprint map, which contains WiFi gradients of the environment and is stored in the cloud. Afterwards, the GIFT engine is executed. GIFT is compatible with site survey[166][189], crowdsourcing [190] and calibration methods [191][192]. GIFT engine compares the RSS with Gmap and estimates the location with motion detection module and EPF. The author also implemented GIFT on mobile devices and conducted extensive experiments in a five-storey building and achieved 80% localization accuracy of average 5.6m with dynamic WiFi signals.

7) CSI with SVM Model: Zhou et al. [118] proposed a DFL system based on WiFi channel state information (CSI) and Support Vector Machine (SVM). The author modeled device-free presence detection as a classification problem and DFL as a regression problem [193] establishing a nonlinear relationship between CSI fingerprint and location using CSI data without considering the complex environment. SVM is proposed for processing CSI data to achieve presence detection. The process flow is as follows: CSI data collection, feature extraction, model training to form presence detection classifier and the relationship between CSI and then the location is established, as shown in Figure 26. The noisy WiFi channels are dealt with through density-based spatial clustering on CSI data. Principle Component Analysis (PCA) is used to reduce the dimensionality of the data, thus reducing computational complexity. Evaluation of this model was done in two experimental setups in the research laboratory and a meeting room. Localization accuracy obtained were 1.22m and 1.39m respectively in which the detection precision is more than 97%.

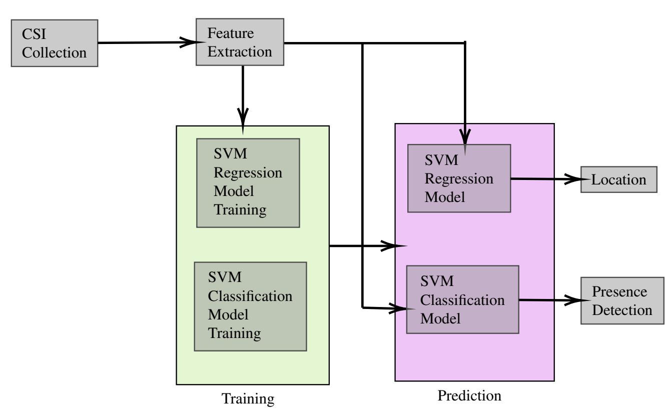

Fig. 26. CSI with SVM[118]

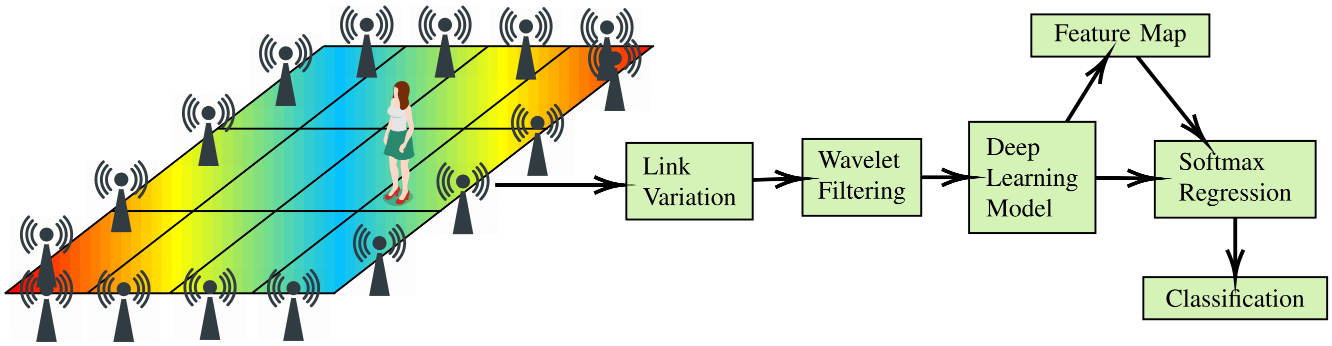

Fig. 27. Deep Learning based DFL system[121]

8) Machine Vision Methods: A real-time DFL system for multiple objects is suggested by Bocca et al. [119] based on machine vision approach. This method is a modification of Radio Tomographic Imaging (RTI), aptly functioning in real-time scenarios. In this model, the author combines RSS measurement of different frequencies for each link. This is, in essence, a fade level of the weighted average method. The method uses the ellipse model to show weight and the image is reconstructed with the regularised least-square method. Change propagating model is adopted from the Wilson et al. [79] model. The author suggested different methods of processing and tracking of multiple objects based on thresholding, Kalman tracking, clustering, etc. This real-time DFL model is tested in three different environments and obtained an average tracking error of 0.45m, 0.46m and 0.55m for two, three, and four targets respectively.

9) Conditional Random Field based Markov Model: The Conditional Random Field based Markov Model is for multiple object localization is presented by Sabek et al. [120]. This model combines the Markov model with the conditional random field to form a probabilistic energy minimization framework to capture the spatial and temporal relationship between the targets. This model uses the cross-calibration technique to reduce calibration overhead, even in multiple object localization scenarios. The author formed an energy minimization framework for this model which further increases accuracy and energy efficiency. The system architecture of the model is outlined in Figure 25. The operation of this method has an offline training phase and an online tracking phase. In the offline training phase, the RSS readings are collected followed by device-free fingerprint construction. In the online tracking phase, energy minimization framework is implemented with the sensed RSS reading with the previous offline fingerprint. The author verified this method with two scenarios of 114 m^2 residential apartment and 130 m^2 office building. In both the environmental setting 25 fingerprint locations were sampled. The authors implemented 17 and 22 independent test locations for residential apartment and office building environment respectively. Both scenarios gave good results, with 1.1m localization accuracy obtained in different test cases. They further compared median error with other DFL systems and concluded that their system is 35% more accurate.

10) Deep Learning: The DFL systems are selected for localization, activity recognition and many other applications as well. This method analyses the wireless links and estimates the target location without embedding any device to target. This method poses a critical problem of characterizing the link property for target localization. Wang et al. [121] proposed a Deep-Learning based approach for realising DFL systems with universal and discriminative features from the wireless links to localize the target as shown in Figure 27. The author developed a Sparse Auto-Encoder network to learn a discriminative feature from the wireless link. These features are merged into a Softmax Regression-based framework to estimate location, gesture, activity recognition simultaneously. The model was experimentally verified with 802.15.4 Zigbee hardware in the cluttered indoor laboratory and an apartment scenario. Both time domain and frequency domain features were considered and analysed. The proposed model has a wavelet filter module, a deep learning feature extraction module and a classification module based on softmax regression. RSS from the link is first measured and applied wavelet transformation [194] to denoise signal is used. Features from this signal are extracted using a Deep Learning model to build the feature map. The map further trains the parameters of the softmax regression classifier [195]. During the offline phase, the parameters are learned using a Deep-Learning model and Softmax Regression model. In the online phase, the feature of the signal links are extracted using Deep Learning model followed by location estimation by Softmax Regression Classifier. The author validated this model with the two scenarios for localization, gesture recognition and activity recognition simultaneously with a localization error of 0.85m and 0.88m in cluttered indoor lab and apartment respectively when using eight sensor nodes.

11) Dictionary Learning: Li et al. [122] proposed a dictionary learning based Difference of Convex (DC) programming to solve the DFL system localization problem. The author suggested the target in a monitoring area can be estimated from the obstructed RSS measured data using dictionary learning. The author formulated the DFL problem as a non-convex optimization problem and adapted the minimax concave penalty for solving it using DC programming. A tracking neighborhood rule is also proposed by the author which can be augmented with the path tracking task to improve the localization accuracy. Under noisy conditions, this rule

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provides a good localization accuracy.

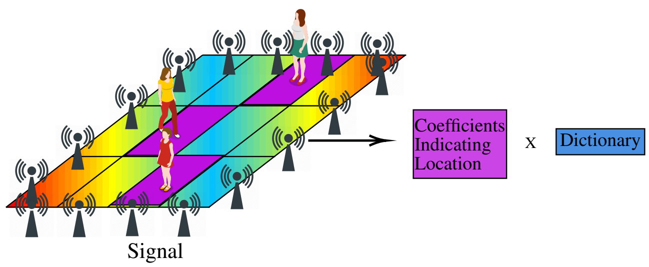

Fig. 28. Dictionary Learning

In the DFL system, the link obstruction information is learned and formulated as a sparse representation model as shown in Figure 28. The sensor nodes broadcast throughout the monitoring area. RSS is sensitive to environmental condition so may change due to humidity, temperature, etc. Hence, changes in the propagation parameters affect the receiver gain of the sensor nodes [169]. Compared to the actual obstruction incidents, the total number of links in the grid is very high, so it manifests as a sparse combination. The author did not derive a direct solution, rather they suggested sparsity-enhanced regularization method. The concept has experimentally validated the method with the real-world dataset of 21 x 21 ft^2 area with 12 sensor nodes with more than 92.86% localization accuracy.

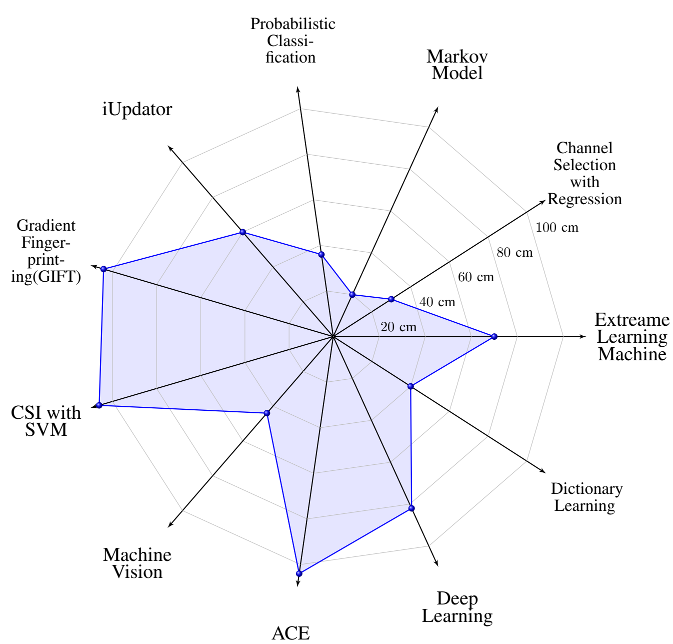

Fig. 29. Comparative Analysis of Localization Error of Training based DFL Approach

B. Summary and Insight

A comparative analysis of training based DFL system is plotted in Figure 29. From the plot, the Markov model based DFL system is found to be more efficient with the accuracy of 0.198m average localization error. There are two types of database generated based on CSI and RSS data. A majority of the approaches follow the RSS method of estimation due to its low cost and complexity. The comparative research findings and their critical analysis is presented in Table III. Probabilistic Classification, Channel selection with regression and dictionary learning approach are excellent candidates for future research work due to their versatile applications and robustness to environmental changes with reasonable accuracy.

VII. Backscattering Method For Device Free Localization

A. Backscattering Models

Backscattering method uses reflection from the environment that RF sensor transmission signals naturally produce to trace for a reflecting object. Analyzing those reflected signal the object location is estimated. The existing backscattering approach of device-free localization is explained below and presented in Table IV

1) WiFi-Scattering, WiVi & WiDeo: WiFi-based scattering uses existing infrastructure for DFL systems. These methods are cost-effective. Motion detection is a prerequisite for various WiFi based DFL systems[60]. Feature extraction based methods motion detection and moving variance have been proposed for motion detection. Moussa et al. [71] suggested Maximum Likelihood estimator for DFL system for smart environments. The detection is improved by an RSS feature extraction system[81][70] from environmental changes or CSI [196][197]from physical temporal variance. WiFi CSI based human detection system [198][152] exploits multipath propagation to extend detection range of a link. Breadth detection based human localization is proposed by Wu et al. [199]. CSI based methods are resistant to variance in environmental changes.

WiVi[123] is WiFi enabled technology to detect moving objects behind closed doors or through walls. WiVi uses Inverse Synthetic Aperture Radar (ISAR) technology for multiple object localization and their motion with direction. WiDeo[124] is a backscattering approach for WiFi infrastructure. The access point plays the role of a backscatter sensor. The RF sensor receives the reflected RF signal and localizes objects using three major features from the reflected signal. These features are amplitude, ToF and AoA. WiDeo mimics the radar principle from Software Defined Radio (SDR) [200]. The author verified that WiDeo is able to locate five objects with high accuracy compared to the other existing methods.

2) RFID: The RFID technology based DFL systems attaches RFID tags in the specified points of the deployed region. An RFID reader transmits the signal, which passes to RFID tags through scattering by the objects. The tags then modulate the RF signal indicating the presence or absence of the object in the specified region. An RFID reader receives this scattered signal and estimates the location of the object. This scattering technique detects moving objects. The range of communication in RFID scattering systems is around ten meters which are further increased by increasing sensitivity [129] of RFID reader. RSS fluctuation based RFID tracking system TagTrack [67] is developed by Ruan et al. which uses a Hidden Markov Model for statistical prediction of target

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TABLE IV. Backscattering Method

Research Work	System	Deployed Environment	Deployment Range	No.of Sensor Nodes	Measured Physical Quantity	Localization Accuracy	Complexity	Research Findings
[124]	WiDeo	Simulated using C and Matlab	Variable	Variable	WiFi Scattered RSS	median error less than 7cm.	Polynomial time	The proposed method mines the WiFi backscattered radio signal and localizes upto five desired object.
[125]	COTS-RFID	Indoor	WiFi Range	tags placed 1m apart	RSS	median error 21.5cm	Polynomial time	Author proposed a method to extract reflected backscattered signal, further localize and track using Hidden Markov Model(HMM).
[126]	UWB	Indoor	10m x 10m (lab)	13 transmitter and 2 receivers.	UWB signal Power	0.27-0.94.m rms error	Linear time but high hardware cost	Differentiate low frequency signal against the background signal, which was affected by humans. From this low frequency signal, the human presence is detected.
[127]	mTrack	Object tracking	1m	≥ 3	Phase/RSS	8mm mean error.	Polynomial time	A novel millimetre wave radio tracking system which uses beam scanning mechanism.
[128]	Doorjamb	Indoor	room	7	Ultrsonic reflected signal	90% room level tracking accuracy	Polynomial time	Ultrasonic range finders based signal processing techniques to localize human position and motion.
[129]	D-Watch	Indoor(library, lab, hall)	9m x 12m(lab), 7m x 10m (library), 7.2x10.4(hall)	8 antenna array with half wavelength space	AoA	median error 16.5cm(library), 25.5cm (lab), 31.2 cm (hall)	Moderate computing cost with high hardware cost	This method uses angle of arrival information from the RFID tags backscatter signal. The backscatter signal is processed with P-MUSIC algorithm capable of multiobject localization.
[130]	UHF-RFID	indoor	20 m^2	Numerous Passive Tags	RSS Variations	0.64m average error.	$O(TS^2)$,Where T is number of rssi vector and S is number of location state,S=26	The author uses passive RFID tags for dtermining the location with maximum probability using supervised learning models. Further, this location construct and emission matrix is used to approximate-track object using Hidden Markov Model.
[131]	Wideband	Simulation and Model	Different Case Study	Variable	Ultrawideband Signal	0.86-1m rms error	NP-hard with different solution approach	A counting based sensor radar is developed which uses wideband signal backscattering.
[201], [202]	Optical Method	Simulation and Prototype	Indoor Scenario	Variable	Image based	Moderate	High	3d model based localization system developed with optical signals, which tends to be computationally efficient.

objects showing 98% of accuracy. RF backscattering through wall scenario using an antenna array of RFID tags called Tadar[125] is proposed by Yang et al. The author models the object motion using Hidden Markov Model and trajectory estimation is done with a Viterbi algorithm. It came up with the localization error of 7.8-20 cm in the indoor scenario. A tiling strategy for RFID readers and tags have been deployed by Kuska et al. [203] for geometric DFL system to locate human beings. Shi et al. [204] replaced the active RFID with passive RFID system for low maintenance, low cost, low scalability, and easy deployment.

3) D-Watch: The RFID tag and reader-based approach are used further in D-Watch [129] with AoA based information processing to estimate the location of the object using backscatter. To locate an object, this system requires at least two readers and multiple tags (around fifty). The angle is estimated from the power drop at the respective direction due to shadowing of the path between tag and reader. Applying triangulation of this angle the location is estimated. The power drop is calculated with MUSIC(MUltiple SIgnal Classification) algorithm [129]. The position of the tags do not have any influence on localization itself; hence there is less deployment cost of this system. However, some tags with direct path angle require prior deployment positioning only to reduce random phase offset. The author deployed this system in 70 m^2 area and reported a 16.5 cm median error for human localization.

4) UWB: Ultra-WideBand (UWB) technologies have higher bandwidth than other technologies which get more precise channel impulse response for narrowing down the target. UWB technologies are more accurate than RSS based method and exhibit less hardware complexity than AoA based antenna array systems. However, the UWB systems are short-range systems due to their ability to send low energy signals. A DFL based human localization scheme based on breathing detection is developed by Yarovoy et al. [205] in the 1-12GHz band using UWB. An outdoor environment based human localization system is developed by Chang et al. [206]. His modified method is for tracking two people [207]. Furthermore, he developed a system to distinguish and localize human entities from other moving objects[208]. A calibration-less DFL system for locating humans was developed again by Kilic et al. [209]. In this method, a likelihood ratio between the received signal power and signal power in human free reflection is compared to locate object position. Further, the author developed four UWB radio based DFL system[126] with errors of 12-180cm in indoor scenarios.

5) mTrack: RF-based scattering principle of DFL systems relies highly on the reflection property of the RF signal. The signal whose wavelength is smaller than the object cannot easily penetrate the object. This property is utilized for achieving maximum reflection but for the traditional ISM band 2.4-5GHz. is not suitable for better scattering based localization. Wei et al. [127] proposed a 60GHz radio standardized with IEEE 802.11ad based tracking system called mTrack. mTrack uses the electronically steerable high directional beam with high sensitivity, tracking the smallest change in object location. It uses both RSS and phase measurement from the scattered signal, and can be realized with one transmitter and two receivers. In this method, the object is located by estimating reflected signals from the relative angle. The author has achieved a localization error below 8mm with a range of just 1m due to the high frequency. Hence this technology can be applicable for localizing small objects, biomedical in-body tumor localization and wireless transcription scenarios.

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6) Ultrasonic Scattering: Ultrasonic based DFL systems act as the supporting system for smart world applications like thief detection, safety and security purposes. This DFL system uses scattering techniques for localization. Consecutive ultrasonic signals are sent in a periodic interval and ultrasonic sensors record the echo by the objects. These echo signals are utilized for localization estimation of objects. A tracking algorithm based on movement patterns is used for localizing humans using ultrasonic DFL systems. Hnat et al. proposed an ultrasonic DFL system for room-level tracking of human beings [128]. The author presented this method as being capable of estimating location as well as height and direction of movement of humans in indoor scenarios with an average localization accuracy of 90%. The ultrasonic sensors are costly which gives a high deployment cost and is thus less popular for commercial applications.

7) UHF-RFID: The RFID based DFL systems are seen as attractive, having low cost, low maintenance and being energy efficient due to passive tags. Ultra-high frequency passive radio-frequency identification (UHF-RFID) tags based scattering for DFL systems was developed by Wenjie et al. [130], taking advantage of supervised classification with data-driven models to quantify the RSS distribution. This DFL system further works as the tracking beacon with the application of multivariate Hidden Markov Model and kNN. Hidden Markov Model for probabilistic estimation of learned localization to construct emission matrix of human models for continuous tracking. In this model, the learning pattern for each iteration can be modified by the system. That makes this model computationally efficient and accurate. The author verified this method with the meticulous experiment in two scenarios with more than 94% accuracy and mean localization error of 0.64m.

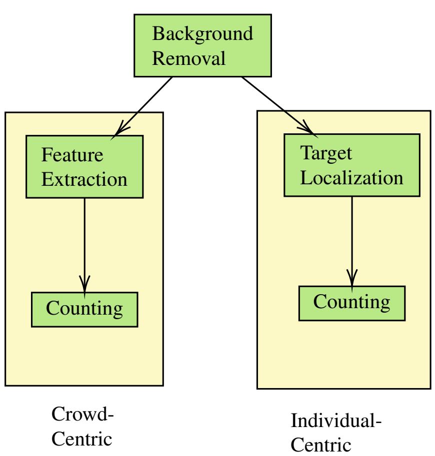

Fig. 30. Wideband Scattering based DFL system[131]

8) Wideband Scattering: DFL using wideband scattering method have applications in counting people and things called crowd-counting in a monitoring area. This Wideband scattering based DFL enables applications in smart buildings, public safety, intelligent transportation for the advancement of the smart world. Bartoletti et al. [131] proposed a mathematical framework for a device-free counting system. This method first uses wideband signal backscattering using model order selection followed by low-level feature selection for counting of the human elements. Low-level feature extraction methods give lower computational complexity in this method. The author verified this method with realistic operating conditions. This is a counting system based on Sensor Radars (SRs). Two scenarios were developed in this work: first individual-centric, based on model order selection and second crowd-centric, based on energy-detection as shown in Figure 30. Energy detection is used for counting where energy samples as a function of the number of targets applicable for only wide-band and ultra-wideband RF signals. The individual-centric approach localized individual targets, but proved to be much more computationally complex then crowd-centric approach. The author further directed that the crowd-centric approach applies to smart world device-free localization scenarios due to its ability which is independent of the number of targets.

9) Optical Methods: In the outdoor scenarios, the GPS fails to work near the building and urban canyons. In those scenarios, the image-based localization system typically gives high localization accuracy. Similarly, GPS signal is very weak in indoor scenarios. The image-based methods promise to give better result in those scenarios. Lu et al. [201] introduced a technique that can build 3D structure from motion pattern captured by a video camera. To this end, the authors developed a system to track people in video feed by using optical flow techniques. Further, a graph matching approach is suggested by the author for estimating camera images. Moreover, the authors experimentally prove the effectiveness of the technique, in terms of localization accuracy and speed, in an indoor mapping context.

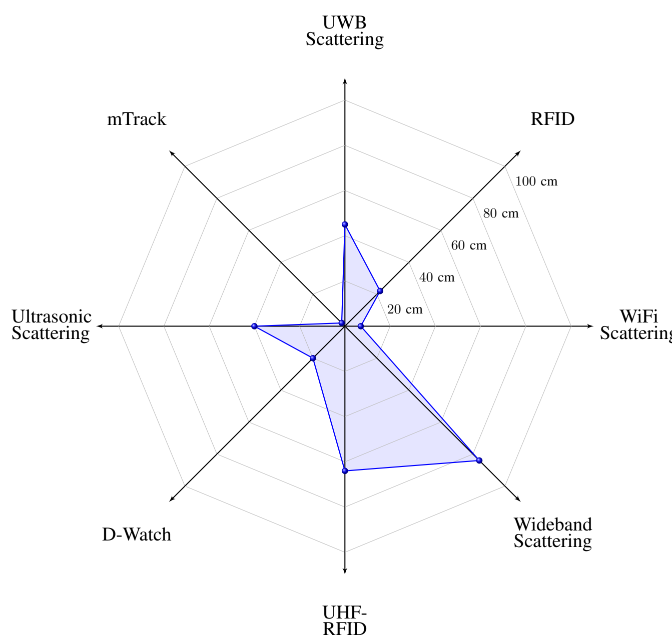

Fig. 31. Comparative Analysis of Localization Error of Backscattering Approach

B. Summary and Insight

The scattering based DFL systems is showing a high accuracy due to the adoption of radar-based technologies.

The reviewed technologies proposed attaining an accuracy between 8mm to 80cm. A spider plot is drawn in Figure 31 to comparatively measure the different system in the light of localization accuracy. From the analysis, it is deduced that WiFi scattering and mTrack methods have the highest accuracy with low average localization error below 20cm. Though wideband scattering and UHF-RFID have very lowest cost systems, these give low localization accuracy comparatively with other methods. Hence for smart world application, mTrack can apply to in-body localization in Body Area Networks. However wideband, Ultra-Wideband, D-watch, WiFi scattering and Ultrasonic based DFL system is applicable in the localization of indoor scenarios. The critical analysis is shown in Table IV.

VIII. Lessons Learned

To reflect on the lessons learned, this section presents overall comparative analysis of the device free localization (DFL) techniques. For simplifying the comparative understanding related to accuracy range and computational complexity of different DFL techniques, we have included the details on the same in Figure 32. One of the key observation, also depicted in Figure 32, is that WiFi scattering and statistical subspace variance method outperforms other methods. While the training-based approaches have reduced in complexity, from highly complex to comparatively lower complex system, scattering and RADAR based DLF methods have been the preferred choice due to its accuracy. As some of the smart world applications demand high accuracy, e.g., 10 cm with low computational and hardware complexity, new classes of RFID-based DFL systems and methods have evolved. Though RFID-based DFL systems and methods can offer improved accuracy, they are not that effective when subjected to heterogeneous indoor IoT networks.

Given the proliferation of smart world applications, from smart healthcare to smart cities, next-generation localization systems and methods need to cater for multitude of heterogeneous environment. It is natural to believe that developing next generation of hybrid localization methods, that combines localization method with an active learning technique, will be a viable alternative for handling the heterogeneity of future smart applications. Training-based hybrid DFL methods, although have unique ability to learn different deployment scenarios and environments, do not perform efficiently when deployed in a new environment. To overcome such limitations, periodic model calibration and re-training, which can be tedious and time consuming, is highly recommended. As very nascent literature is available in context of hybrid localization methods, this area of research is expected to receive significant attention from research community.

We also found that power consumption is a major issue in those DFL methods that are based on Radio Frequency (RF) network. For instance, scattering and RADAR based DFL methods can provide centimeter grade accuracy, they are highly power consuming due to the need of sending and receiving large volume of RF signals. Hence, one of the future research directions could be how to make RF-based DLF methods more energy efficient while not compromising on its accuracy. To summarise, the LBS-based DFL methods also have good potential to be adopted in context of IoT-based smart world applications.

Implementing DFL based system for localization in smart heterogeneous network warrants additional hardware. However, this is in contradiction to the original requirement of smart world application, which prefers infrastructure-free DFL deployment environment. To balance these conflicting requirements, one of the possible alternatives could be to deploy the DFL methods within the WiFi router/switch chipset. In our view, future research investigations will focus on some of the aspects discussed above.

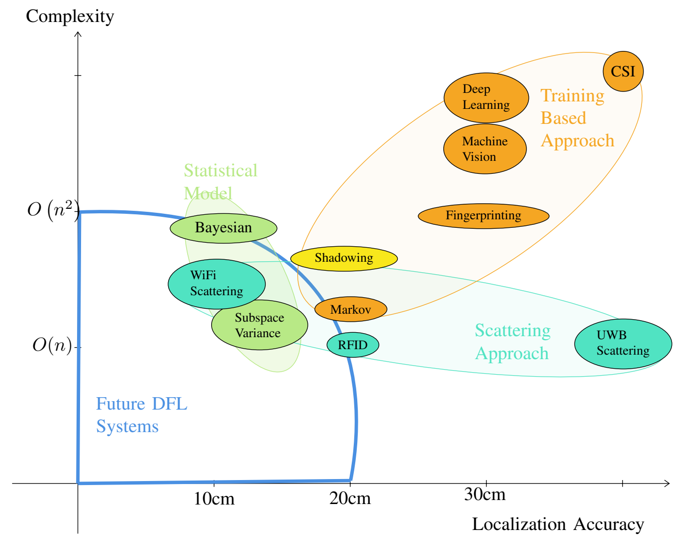

Fig. 32. Lessons Learned

IX. Applications, Open Issues and Future Direction

The device-free localization serves a huge percentage in location-based services in smart world domains. The application, related issue and future direction of the research are summarized in the following Table V. The smart word domains are categorized as smart home, smart city, energy efficiency, Intelligent Transportation System(ITS), Industry, Emergency Services, Sports and Retail. Challenges and future research of each domain are analyzed in the following subsections.

A. Application

Automatic monitoring and control in the Smart World scenario are possible with the development of networking and localization techniques. These technologies provide intelligence and comfort to disabled and older adults[25] [44] [141]. Control of heating, lighting, air-conditioning has been implemented already for smart homes. The DFL system can enhance these smart systems by providing location information. The existing smart systems can use this location information to provide more robust control. For example, the room heating and air conditioning can better be controlled if the information about the number of occupants and their body temperature is available [150][199][154]. For a room with a very high number

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TABLE V. Application,Open Issue and Future Research

Smart World Domain	Application of DFL	Challenges	Future Research
Smart Home	1-Intrusion Detection[89] 2-Activity Recognition[210][211]	1-Threat and Security[212][213][214] 2-Anomaly Detection 3-Optimal Sensor Deployment	1-Environmental impact modelling in RF network[156] 2-Robustness under irregular environment.[157] 3-Centimeter grade accuracy DFL system[28] [27] [124] [125]
Smart City	1-Border Control[215] 2-Surveillance System[79] [216]	1-Anomaly Detection	1-CSI based DFL system[154] 2-Ubiquitous monitoring
Energy	1-Occupancy Detection[150][199] based Automatic Control[154]	1-Anomaly Detection of Static and Dynamic Object. 2-Multi-object Detection.[110][28]	1-Heart beat based human localization and counting.[26] 2-breathing detection based human localization and counting.[151]
ITS	1-User Identification[217] [218]	1-Threat and Security.[214]	
Healthcare	1-Elderly Care[25] [44] 2-Ambient Assisted Living[141]	1-Threat and Security	1-Deep learning based data modelling for DFL
Industry	1-Occupancy Detection[199] 2-Individual Counting[219] [220] 3-Industrial Safety[221] [222] 4-Industrial Risk Monitoring	1-Threat and Security[214] 2-Multi-object detection[110][28]	1-Human detection based on motion pattern using Deep learing[223] [224]
Emergency Services	1-Rescue Mission[164] [225] 2-Border Control[215] 3-Fire Rescue Mission	1-Multi-object detection[110][28] 2-Hardware and Maintenance[100]	1-Scattering based Radar Development 2-Wi-Fi CSI[154]
Sports	1-Gesture Recognition[226][227] 2-Activity Recognition[153] [228]	1-Localize object without any activity[229][156]	1-Vital sign /activity classification
Retail	1-Shoppers Behaviour Recognition[230][228]	1-Threat and Security	1-RFID Localization[224][125]

of occupants, if it results in increasing temperature then the building heating system can adjust the conditioning to lower levels of cooling. In the case of no occupants, the conditioning system will shut down and fall into power saving mode. The DFL system helps to collect this environmental information which enhances the existing smart control systems.

DFL system is highly essential for intruder detection and security applications too [89] [230]. If the system locates any activity in an entrance to a specific object other than the main entrance, like the balcony window or back door, then it processes this information and compares it to the movement information defined in the database in the system profile. The DFL system analyzes location, movement and activity. For cases when the intruder activity detected is classified very uncommon and not defined in the system profile, it will activate the alarm routine. Hence, the safety and security of the smart building are vitally improved by the DFL system.

The location of intruder and victims are critical in hostage situations. DFL systems are the only option for localizing and tracking victims and intruders during a rescue operation [15]. Military and special operation forces can evoke decisions based on such crucial location information provided by DFL system. Maas et al. [216] studied rapidly deployable RF sensor network for localization and self-calibration. In a hostage situation, DFL system measures RSS on all the links and processes them in real-time to show the location of an individual and an object in a building. This gives the situational information about the safety of the building or which part of the building is safe for entrance or initiating point to a rescue operation [164] [225].

In natural disaster scenarios too, like earthquake, fires, flooding, etc., the distressed civilians, trapped or otherwise, need to be localized for providing emergency aid by emergency responders. Fisher et al. [225] demonstrated an efficient way of emergency responders action with the help of DFL system. These responder systems estimate the survivors as well as keep track of the responders in action with the help of DFL systems in a inaccessible situation. Any such disastrous situation can be avoided with the help of DFL systems, including monitoring the presence of toxic gases or vibrations in the building structures ubiquitously, and so on. In a fire rescue mission, the firefighter seeks the location information of the victim as well as the best possible safe route for rescue. These routes are dynamic, and real-time monitoring of the safest route as well as the affected space is pivotal to the success of such activities and is possible with DFL systems.

The safety of the professional individuals in an industrial area is a significant concern and it is only possible with the ubiquitous monitoring of the workers in industrial scenarios like manufacturing plants, construction sites, etc. [221] [222]. DFL systems continuously monitor the interference and individuals to recognize hazards and related activities in the area of deployment. Edirisinghe et al. [221] developed a DFL system to identify the risk zone in a construction site scenario. They

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developed different geographical work zones on the site and defined potential hazards in the zone. Further, they outlined the risk profile of each zone for different activities. It was experimentally verified that the DFL system is effective for indoor and outdoor scenarios of different construction phases. Edirisinghe et al. [221] further proposed DFL based detection and risk monitoring system in different scenarios for the ability to detect human, vehicle and different activities. However, their proposed system, unfortunately, gives a false alarm and misses in different scenarios.

The DFL system considerably enhances the healthcare and assisted living scenarios by interpreting the daily work of patients and individuals. If there are any abnormalities in the behaviour traced in subjects, then the health specialist is notified to visit the individual. A finite state machine (FSM) based DFL system is proposed by Kaltiokallio et al.[44] for elderly care scenario. This approach extracts higher-level information from the localized individual to estimate health condition. Bocca et al. [141] developed Ambient Assisted Living (AAL) system with the help of device-free approach. DFL system does not require the tracked entity to have an embedded device. Hence, it is well applicable to healthcare scenarios. Due to the ubiquitous nature of device-free based localization approach, it is gaining enormous interest in localization technologies. The wide applicability of DFL is shown in Table V.

B. Open Issues and Challenges

The device-free localization approach opens up a diverse set of application domains, as explained in Table V, and immense research interest is gaining momentum in this field. However, realising these technologies in appropriate smart world scenarios needs further deeper development. Though DFL is a novel localization approach, challenges encountered in this direction are numerous, like anomaly detection, hardware costs, security, scalability, inter-operability, deployment overhead, etc. as shown in Table V.

Object movement or other physical information is not available in device free scenarios in contrast to device based scenarios. The identity or type of the object to be localized is a challenging task. DFL systems should be able to differentiate the target object from all other objects in the field. Hence, anomaly detection is a significant step before localization in device free approach, and there are huge chances of misdetection or false alarm as well. One possible solution to this problem is the application of Pattern Recognition, commonly used in computer vision to differentiate objects. It has been inferred that there is a need for similar technology in DFL system by which uniquely defined features specify the target object, distinguishing it from all other objects.

Counting of localized objects plays a vital role in monitoring crowds in communities for rescue operation or safety and precaution, public social spaces like shopping malls or exhibitions and associated safety mechanisms in place, and similar situations. Some research work reported Percentage of nonzero Element approach [219] in CSI to locate and count the human population in different scenarios. Still, in wireless network infrastructure, differentiating static and moving objects followed by localization and counting is an open research challenge.

Multi-object tracking is another significant and difficult-to-solve challenge. It even drastically reduces the performance of the DFL system for indoor scenarios, where the RSS or CSI variations are strenuous to calibrate even in case of the multipath effect of the signal. A massive amount of multiple link calculations or specialized hardware are required for existing successive cancellation approach [110] [28] of DFL system where the individual object's impact is separated from the whole. The available DFL based simultaneous multi-tracking system is only capable of localizing less than ten objects. This solution is only acceptable for smaller scenarios. For real-world smart world applications like conferences, shopping malls, conventions and large social gatherings, exhibition centres, etc., the present methods fail to achieve multi-object localization. This aspect emerges a potential open challenge, and scattering based radars and Wi-Fi CSI method may solve this challenge in the future.

Deployment strategies enormously impact the localization performance of a specific setting. The detection accuracy in the indoor scenario is profoundly affected by moving the ceiling sensor nodes to the floor. Hence, an optimized deployment strategy is a necessity for better accuracy in DFL systems. Open research issues here are the minimization of the sensor nodes in number with maximum coverage and reaching the least number of dead spots in the deployment region. The deployment cost varies from different approaches of DFL systems, for example, the training based and fingerprint approach requires lesser sensors compared to the radio grid-based approaches. Deploying more sensors in multiple scenarios require high cost and if the battery-power sensors are deployed the additional augment energy requirement issue arises in the long run. The RF sensor based localization and occupancy detection system renders enough accuracy in deployed infrastructure but a major issue of power consumption pops up.

The primary objective of DFL systems is to localize objects without embedding sensor devices in the target object. It is a form of sensing module design which is enormously extended into different utility contexts like activity detection, monitoring, location-aware activities, etc. [231][229]. There is still a challenge left - to localize objects independent of activities without the use of training modules in commercial wireless and IoT infrastructures.

Scattering based DFL systems for object localization are much more fine-grained and accurate. However, technology makes this approach quite expensive. Military scattering based radar systems of DFL are highly accurate but out of the many future scopes are in civilian and industrial applications. Alternative solutions of SDR based Radar and WiFi-based systems provide accuracy with industrial applicability. Among the scattering methods, the UWB based approach is highly expensive due to UWB transceiver. These technologies costs are dependant mainly on bandwidth, which further depends on localization accuracy. Therefore, finding a low-cost option in this approach is an open challenge. Device-free RFID approach is a low-cost option in this kind of approach [125][100].

The localization accuracy is increased by frequency diversity in industrial and medical wireless networks. The common allocated frequency band of operation of these networks is the Industrial-Scientific-Medical(ISM) band. In indoor scenarios, the network functions in this band, which have a high density of devices and thus needs to tackle interference due to neighboring devices.

The RF-based device-free localization is more advanced and provides privacy over the existing computer vision strategies in activity recognition and presence detection. However, Qiao et al. [214] reported an issue in indoor scenarios of WiFi-based DFL systems where intruders are able to exploit the WiFi to get the critical information of individuals, like their presence and activities which may be misused for criminal intentions. Hence, securing the DFL system is definitely a primary and open challenge for the smart world community.

C. Future Research

Localization systems are designed, calibrated and tested in a standard environment. Sudden changes in the environment can lead to major anomalies in overall accuracy. These environmental effects can be conquered by modeling the object's motion [156] and Doppler shifts [157] for localization and activity recognition. Modelling the environmental impacts towards accurate DFL system is the prospective future work. Work thus requiring to be done has been outlined in Table V.

The lowest device-free localization error achieved in scattering based on radar principle [28][27][124][125] is of a few centimetres. However, for smart world applications of intrusion detection, elderly monitoring, rescue mission and indoor climate control even few centimeter grade errors impact the performance of the DFL systems. The DFL context and its application are lacking context-aware ubiquitous solutions for the smart world setups and its prospective future research. Centimeter grade accuracy in indoor localization and millimeter grade accuracy in in-body wireless networks can render the Smart World components ubiquitously localized for these scenarios.

The CSI based DFL systems are popular due to its structure and its application. This method uses channel frequency response of the link. Different frequencies are prone to different attenuation levels due to frequency selective fading. Wang et al. [90] proposed a LiFS model to filter those bad frequency carriers which are subjected to fading and infer object position in DFL systems. Dimensionality reduction techniques [154][156] like PCA and kPCA methods are effective in efficiently extracting features from CSI measurement to solve the frequency-selective fading problem in DFL units. This approach of device-free systems can so be improved for better localization, activity recognition and detection based applications for the future Smart World. The precise carrier channel frequency estimation is a challenge, and it can degrade randomness of received signals that restricts accuracy in localization as well as Doppler shift of received signals. Luong et al. [232] proposed a frequency synchronization method of the sensor nodes which help better carrier channel frequency estimation.

Accurate feature selection and definition of rules for better prediction of location based on deep learning approach in DFL is a novel approach. Deep learning solved most data modeling challenges and is definitely applicable to different diverse scenarios like speech recognition and computer vision. It can even be further extended to human sensing [223] in device free scenarios. Few works have been reported in the device-based frameworks on RFID technologies[224] which can be followed in device-free scenarios for localization.

Localization of humans or objects based on motion pattern is adopted in many methods. This can be further extended with the vital sign. Localization of humans based on vital sign such as heartbeats [233], breathing [26] [151], etc. holds great potential as future technologies in smart world scenarios.

X. Conclusion

The smart world and its application are enabled by the wireless sensor network technology and its various features. Sensor-less or device-free localization is an advanced application for the smart world using wireless RF sensor technologies. In this technology, the static or moving object is tracked and localized without embedding the object with any sensor or tags. In DFL systems the tracked object need not be aware of the localization system. Hence this system works without the cooperation of the tracked object. It offers a multitude of smart world applications like smart home control, counting and monitoring crowd, military rescue operation, surveillance system, disaster rescue, etc. This paper reviews the existing device-free localization approaches and their application in the domain of the futuristic smart world. There are two primary techniques of DFL: vision-based and radar-based depending upon the attenuation and scattering properties of RF wave used for device-free localization system. Moreover, a vision-based approach is categorized into model-based and training based approaches respectively. A new taxonomy of existing research work is presented alongside comparative analysis of the various methods. The main focus dimensions for comparative analysis includes the model-based, training based and scattering-based approaches. These are well-established dimensions for studying DFL systems. Finally, the application ranges of DFL is discussed, followed by challenges, and innovative future research is drawn and concluded.

References

[1] Y. Masumoto, "Global positioning system," May 11 1993. US Patent 5,210,540.

[2] N. Bulusu, J. Heidemann, and D. Estrin, "Gps-less low-cost outdoor localization for very small devices," *IEEE personal communications*, vol. 7, no. 5, pp. 28–34, 2000.

[3] O. Oguejiofor, V. Okorogu, A. Adewale, and B. Osuesu, "Outdoor localization system using rssi measurement of wireless sensor network," *International Journal of Innovative Technology and Exploring Engineering*, vol. 2, no. 2, pp. 1–6, 2013.

[4] F. Seco, A. R. Jiménez, C. Prieto, J. Roa, and K. Koutsou, "A survey of mathematical methods for indoor localization," in *IEEE International Symposium on Intelligent Signal Processing, 2009. WISP 2009.*, pp. 9–14, IEEE, 2009.

[5] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 37, no. 6, pp. 1067–1080, 2007.

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TABLE VI. List of Abbreviation

Abbreviation	Explanation
AoA	Angle of Arrival
BPNN	Back Propagation Neural Network
cdRTI	Channel Diversity Radio Tomographic Imaging
CRF	Conditional Random Field
CRLB	Cramer Rao Lower Bound
CS	Compressive Sensing
CSI	Channel State Information
CSMA/CA	Carrier Sense Multiple Access with Collision Avoidance
DCP	Difference of Convex Programming
DFL	Device Free Localization
EHIPA	Energy efficient HIgh Precesion Adaptive
ELM	Extreme Learning Machine
ESD	Electronical Switched Directional
FFZ	First Freshnel Zone
FSM	Finite State Machine
GIFT	GradIent FingerprinTing
GMM	Gaussian Mixture Model
GPS	Global Positioning System
GSM	Global System for Mobile Communication
HAC	Hierarchical Agglomeretive Clustering
HMM	Hidden Markov Model
ISAR	Inverse Synthetic Aperture Radar
KLD	Kullback Leibler Divergence
LBS	Location Based Services
LDA	Linear Discriminant Analysis
LiFS	Localization information with Fine-grained Subcarrier
LOS	Line of Sight
MIC	Maximum Independent Column
MIMO	Multiple Input Multiple Output
MUSIC	MUltiple SIgnal Classification
NLOS	Non Line of Sight
PCA	Principal Component Analysis
PGFE	Parameterized Geometrical Feature Extraction
PHD	Probability Hypothesis Density
PRR	Packet Reception Rate
RADAR	Radio Detection and Ranging
RFID	Radio Frequency Identification
RIP	Restricted Isometry Property
ROI	Region of Interest
RSS	Received Signal Strengh
RSSI	Received Signal Strengh Indicator
RSVD	Regularised Singular Value Decomposition
RTI	Radio Tomographic Imaging
SCPL	Sequential Counting Parallel Localization
SDR	Software Defined Radio
SIR	Sampling Importance Resampling
SMC	Sequential Monte Carlo
SR	Sensor Radar
SVM	Support Vector Machine
SVR	Support Vector Regression
ToA	Time of Arrival
UHF	Ultra High Frequency
UWB	Ultra Wide Band
VRTI	Variance based Radio Tomographic Imaging
WBSN	Wireless Body Sensor Network
WKNN	Weighted K-Nearest Neighbour
WSN	Wireless Sensor Network

[6] M. Chen, S. Gonzalez, A. Vasilakos, H. Cao, and V. C. Leung, "Body area networks: A survey," *Mobile networks and applications*, vol. 16, no. 2, pp. 171–193, 2011.

[7] M. Pourhomayoun, Z. Jin, and M. L. Fowler, "Accurate localization of in-body medical implants based on spatial sparsity," *IEEE Transactions on Biomedical Engineering*, vol. 61, no. 2, pp. 590–597, 2014.

[8] D. Schneider, "New indoor navigation technologies work where gps can't," *IEEE Spectrum*, vol. 50, no. 12, pp. 34–39, 2013.

[9] K. Pahlavan, G. Bao, Y. Ye, S. Makarov, U. Khan, P. Swar, D. Cave, A. Karellas, P. Krishnamurthy, and K. Sayrafian, "Rf localization for wireless video capsule endoscopy," *International Journal of Wireless Information Networks*, vol. 19, no. 4, pp. 326–340, 2012.

[10] J. Chen, J. Li, and T. H. Lai, "Trapping mobile targets in wireless sensor networks: An energy-efficient perspective," *IEEE Transactions on Vehicular Technology*, vol. 62, no. 7, pp. 3287–3300, 2013.

[11] S. J. Kim and B. K. Kim, "Dynamic ultrasonic hybrid localization system for indoor mobile robots," *IEEE Transactions on Industrial Electronics*, vol. 60, no. 10, pp. 4562–4573, 2013.

[12] S. S. Saab and Z. S. Nakad, "A standalone rfid indoor positioning system using passive tags," *IEEE Transactions on Industrial Electronics*, vol. 58, no. 5, pp. 1961–1970, 2011.

[13] Y. Zhang, S. He, and J. Chen, "Data gathering optimization by dynamic sensing and routing in rechargeable sensor networks," *IEEE/ACM Transactions on Networking*, vol. 24, no. 3, pp. 1632–1646, 2016.

[14] R. C. Shit, S. Sharma, D. Puthal, and A. Y. Zomaya, "Location of things (lot): A review and taxonomy of sensors localization in iot infrastructure," *IEEE Communications Surveys & Tutorials*, vol. 20, no. 3, pp. 2028–2061, 2018.

[15] N. Patwari and J. Wilson, "Rf sensor networks for device-free localization: Measurements, models, and algorithms," *Proceedings of the IEEE*, vol. 98, no. 11, pp. 1961–1973, 2010.

[16] O. Masoso and L. J. Grobler, "The dark side of occupants' behaviour on building energy use," *Energy and buildings*, vol. 42, no. 2, pp. 173–177, 2010.

[17] F. Manzoor, D. Linton, and M. Loughlin, "Occupancy monitoring using passive rfid technology for efficient building lighting control," in *Fourth International EURASIP Workshop On RFID Technology (EURASIP RFID), 2012*, pp. 83–88, IEEE, 2012.

[18] Y. Agarwal, B. Balaji, S. Dutta, R. K. Gupta, and T. Weng, "Duty-cycling buildings aggressively: The next frontier in hvac control," in *10th International Conference on Information Processing in Sensor Networks (IPSN), 2011*, pp. 246–257, IEEE, 2011.

[19] A. Beltran, V. L. Erickson, and A. E. Cerpa, "Thermosense: Occupancy thermal based sensing for hvac control," in *Proceedings of the 5th ACM Workshop on Embedded Systems For Energy-Efficient Buildings*, pp. 1–8, ACM, 2013.

[20] V. L. Erickson, S. Achleitner, and A. E. Cerpa, "Poem: Power-efficient occupancy-based energy management system," in *Proceedings of the 12th international conference on Information processing in sensor networks*, pp. 203–216, ACM, 2013.

[21] V. L. Erickson, M. Á. Carreira-Perpiñán, and A. E. Cerpa, "Occupancy modeling and prediction for building energy management," *ACM Transactions on Sensor Networks (TOSN)*, vol. 10, no. 3, p. 42, 2014.

[22] J. R. Dobbs and B. M. Hencey, "Predictive hvac control using a markov occupancy model," in *American Control Conference (ACC), 2014*, pp. 1057–1062, IEEE, 2014.

[23] X. Liu, J. Cao, S. Tang, J. Wen, and P. Guo, "Contactless respiration monitoring via off-the-shelf wifi devices," *IEEE Transactions on Mobile Computing*, vol. 15, no. 10, pp. 2466–2479, 2016.

[24] J. Liu, Y. Wang, Y. Chen, J. Yang, X. Chen, and J. Cheng, "Tracking vital signs during sleep leveraging off-the-shelf wifi," in *Proceedings of the 16th ACM International Symposium on Mobile Ad Hoc Networking and Computing*, pp. 267–276, ACM, 2015.

[25] H. Wang, D. Zhang, Y. Wang, J. Ma, Y. Wang, and S. Li, "Rt-fall: A real-time and contactless fall detection system with commodity wifi devices," *IEEE Transactions on Mobile Computing*, vol. 16, no. 2, pp. 511–526, 2017.

[26] F. Adib, H. Mao, Z. Kabelac, D. Katabi, and R. C. Miller, "Smart homes that monitor breathing and heart rate," in *Proceedings of the 33rd annual ACM conference on human factors in computing systems*, pp. 837–846, ACM, 2015.

[27] F. Adib, Z. Kabelac, D. Katabi, and R. C. Miller, "3d tracking via body radio reflections.," in *NSDI*, vol. 14, pp. 317–329, 2014.

[28] F. Adib, Z. Kabelac, and D. Katabi, "Multi-person localization via rf body reflections.," in *NSDI*, pp. 279–292, 2015.

[29] C. R. Anderson, R. K. Martin, T. O. Walker, and R. W. Thomas, "Radio tomography for roadside surveillance," *IEEE Journal of Selected Topics in Signal Processing*, vol. 8, no. 1, pp. 66–79, 2014.

[30] R. M. Buehrer, C. R. Anderson, R. K. Martin, N. Patwari, and M. G. Rabbat, "Introduction to the special issue on non-cooperative localization networks," *IEEE Journal of Selected Topics in Signal Processing*, vol. 8, no. 1, pp. 2–4, 2014.

[31] L.-A. Tang, X. Yu, S. Kim, J. Han, C.-C. Hung, and W.-C. Peng, "Tru-alarm: Trustworthiness analysis of sensor networks in cyber-physical systems," in *IEEE 10th International Conference on Data Mining (ICDM), 2010*, pp. 1079–1084, IEEE, 2010.

[32] A. Muller, A. C. Marquez, and B. Iung, "On the concept of e-maintenance: Review and current research," *Reliability Engineering & System Safety*, vol. 93, no. 8, pp. 1165–1187, 2008.

[33] A. Ipakchi and F. Albuyeh, “Grid of the future,” *IEEE power and energy magazine*, vol. 7, no. 2, pp. 52–62, 2009.

[34] N. Wang, N. Zhang, and M. Wang, “Wireless sensors in agriculture and food industry—recent development and future perspective,” *Computers and electronics in agriculture*, vol. 50, no. 1, pp. 1–14, 2006.

[35] F. Palmieri, M. Ficco, S. Pardi, and A. Castiglione, “A cloud-based architecture for emergency management and first responders localization in smart city environments,” *Computers & Electrical Engineering*, vol. 56, pp. 810–830, 2016.

[36] T. Kitanouma, E. Nii, N. Adachi, and Y. Takizawa, “Smartfinder: Cloud-based self organizing localization for mobile smart devices in large-scale indoor facility,” in *Global Internet of Things Summit (GIoTS), 2017*, pp. 1–6, IEEE, 2017.

[37] Y. Saleem, N. Crespi, M. H. Rehmani, R. Copeland, D. Hussein, and E. Bertin, “Exploitation of social iot for recommendation services,” in *IEEE 3rd World Forum on Internet of Things (WF-IoT), 2016*, pp. 359–364, IEEE, 2016.

[38] J. Bao, Y. Zheng, D. Wilkie, and M. Mokbel, “Recommendations in location-based social networks: a survey,” *GeoInformatica*, vol. 19, no. 3, pp. 525–565, 2015.

[39] T. Sztyler and H. Stuckenschmidt, “On-body localization of wearable devices: An investigation of position-aware activity recognition,” in *IEEE International Conference on Pervasive Computing and Communications (PerCom), 2016*, pp. 1–9, IEEE, 2016.

[40] M. Chen, Y. Zhang, Y. Li, M. M. Hassan, and A. Alamri, “Aiwac: Affective interaction through wearable computing and cloud technology,” *IEEE Wireless Communications*, vol. 22, no. 1, pp. 20–27, 2015.

[41] H. Chourabi, T. Nam, S. Walker, J. R. Gil-Garcia, S. Mellouli, K. Nahon, T. A. Pardo, and H. J. Scholl, “Understanding smart cities: An integrative framework,” in *45th Hawaii International Conference on System Science (HICSS), 2012*, pp. 2289–2297, IEEE, 2012.

[42] J. Ma, L. T. Yang, B. O. Apduhan, R. Huang, L. Barolli, M. Takizawa, and T. K. Shih, “A walkthrough from smart spaces to smart hyperspaces towards a smart world with ubiquitous intelligence,” in *Proceedings. 11th International Conference on Parallel and Distributed Systems, 2005.*, vol. 1, pp. 370–376, IEEE, 2005.

[43] A. Barrat, M. Barthelemy, and A. Vespignani, *Dynamical processes on complex networks*. Cambridge university press, 2008.

[44] O. Kaltiokallio, M. Bocca, and N. Patwari, “Follow@ grandma: Long-term device-free localization for residential monitoring,” in *IEEE 37th Conference on Local Computer Networks Workshops (LCN Workshops), 2012*, pp. 991–998, IEEE, 2012.

[45] K. Caine, S. Šabanović, and M. Carter, “The effect of monitoring by cameras and robots on the privacy enhancing behaviors of older adults,” in *7th ACM/IEEE International Conference on Human-Robot Interaction (HRI), 2012*, pp. 343–350, IEEE, 2012.

[46] T. Teixeira, G. Dublon, and A. Savvides, “A survey of human-sensing: Methods for detecting presence, count, location, track, and identity,” *ACM Computing Surveys*, vol. 5, no. 1, pp. 59–69, 2010.

[47] T. Kivimäki, T. Vuorela, P. Peltola, and J. Vanhala, “A review on device-free passive indoor positioning methods,” *International Journal of Smart Home*, vol. 8, no. 1, pp. 71–94, 2014.

[48] S. Coetzee, C. Baker, and H. Griffiths, “Narrow band high resolution radar imaging,” in *IEEE Conference on Radar, 2006*, pp. 4–pp, IEEE, 2006.

[49] M. Wicks, B. Himed, H. Bascom, and J. Clancy, “Tomography of moving targets (tmt) for security and surveillance,” *Advances in Sensing with Security Applications*, pp. 323–339, 2006.

[50] H. D. Griffiths and C. J. Baker, “Radar imaging for combatting terrorism,” in *Imaging for detection and identification*, pp. 29–48, Springer, 2007.

[51] E. Paolini, A. Giorgetti, M. Chiani, R. Minutolo, and M. Montanari, “Localization capability of cooperative anti-intruder radar systems,” *EURASIP Journal on Advances in Signal Processing*, vol. 2008, no. 1, p. 726854, 2008.

[52] L. Reggiani, M. Rydstrom, G. Tiberi, E. G. Strom, and A. Monorchio, “Ultra-wide band sensor networks for tracking point scatterers or relays,” in *6th International Symposium on Wireless Communication Systems, 2009. ISWCS 2009.*, pp. 1–5, IEEE, 2009.

[53] H. Godrich, A. M. Haimovich, and R. S. Blum, “Target localization accuracy gain in mimo radar-based systems,” *IEEE Transactions on Information Theory*, vol. 56, no. 6, pp. 2783–2803, 2010.

[54] Y. Xu, S. Wu, J. Shao, J. Chen, and G. Fang, “Life detection and location by mimo ultra wideband radar,” in *14th International Conference on Ground Penetrating Radar (GPR), 2012*, pp. 80–84, IEEE, 2012.

[55] J. Wilson and N. Patwari, “See-through walls: Motion tracking using variance-based radio tomography networks,” *IEEE Transactions on Mobile Computing*, vol. 10, no. 5, pp. 612–621, 2011.

[56] O. Kaltiokallio, M. Bocca, and N. Patwari, “Enhancing the accuracy of radio tomographic imaging using channel diversity,” in *IEEE 9th International Conference on Mobile Adhoc and Sensor Systems (MASS), 2012*, pp. 254–262, IEEE, 2012.

[57] K. Gaikovich, P. Gaikovich, Y. S. Maksimovitch, and V. Badeev, “Pseudopulse near-field subsurface tomography,” *Physical Review Letters*, vol. 108, no. 16, p. 163902, 2012.

[58] M. Khaledi, S. K. Kasera, N. Patwari, and M. Bocca, “Energy efficient radio tomographic imaging,” in *Eleventh Annual IEEE International Conference on Sensing, Communication, and Networking (SECON), 2014*, pp. 609–617, IEEE, 2014.

[59] R. Priyadarshini and R. Mehra, “Quantitative review of occupancy detection technologies,” *Int. J. Radio Freq*, vol. 1, pp. 1–19, 2015.

[60] M. Youssef, M. Mah, and A. Agrawala, “Challenges: device-free passive localization for wireless environments,” in *Proceedings of the 13th annual ACM international conference on Mobile computing and networking*, pp. 222–229, ACM, 2007.

[61] N. Pirzada, M. Y. Nayan, F. S. M. F. Hassan, and M. A. Khan, “Device-free localization technique for indoor detection and tracking of human body: A survey,” *Procedia-Social and Behavioral Sciences*, vol. 129, pp. 422–429, 2014.

[62] V. Garg and M. Jhamb, “A review of wireless sensor network on localization techniques,” *International Journal of Engineering Trends and Technology (IJETT)*, vol. 4, no. 4, 2013.

[63] M. Bouet and A. L. Dos Santos, “Rfid tags: Positioning principles and localization techniques,” in *1st IFIP Wireless Days, 2008. WD’08.*, pp. 1–5, IEEE, 2008.

[64] C. Hekimian-Williams, B. Grant, X. Liu, Z. Zhang, and P. Kumar, “Accurate localization of rfid tags using phase difference,” in *IEEE International Conference on RFID, 2010*, pp. 89–96, IEEE, 2010.

[65] B. Cao, Y. Ge, C. W. Kim, G. Feng, H. P. Tan, and Y. Li, “An experimental study for inter-user interference mitigation in wireless body sensor networks,” *IEEE Sensors Journal*, vol. 13, no. 10, pp. 3585–3595, 2013.

[66] G. Deak, K. Curran, and J. Condell, “A survey of active and passive indoor localisation systems,” *Computer Communications*, vol. 35, no. 16, pp. 1939–1954, 2012.

[67] W. Ruan, L. Yao, Q. Z. Sheng, N. J. Falkner, and X. Li, “Tagtrack: Device-free localization and tracking using passive rfid tags,” in *Proceedings of the 11th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services*, pp. 80–89, ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2014.

[68] K. El-Kafrawy, M. Youssef, and A. El-Keyi, “Impact of the human motion on the variance of the received signal strength of wireless links,” in *IEEE 22nd International Symposium on Personal Indoor and Mobile Radio Communications (PIMRC), 2011*, pp. 1208–1212, IEEE, 2011.

[69] J. S. Turner, M. Ramli, L. Kamarudin, A. Zakaria, A. Shakaff, D. L. Ndzi, C. Nor, N. Hassan, and S. Mamduh, “The study of human movement effect on signal strength for indoor wsn deployment,” in *IEEE Conference on Wireless Sensor (ICWISE), 2013*, pp. 30–35, IEEE, 2013.

[70] M. Seifeldin, A. Saeed, A. E. Kosba, A. El-Keyi, and M. Youssef, “Nuzzer: A large-scale device-free passive localization system for wireless environments,” *IEEE Transactions on Mobile Computing*, vol. 12, no. 7, pp. 1321–1334, 2013.

[71] M. Moussa and M. Youssef, “Smart cevices for smart environments: Device-free passive detection in real environments,” in *IEEE International Conference on Pervasive Computing and Communications, 2009. PerCom 2009.*, pp. 1–6, IEEE, 2009.

[72] R. J. Pirkl and G. D. Durgin, “Quasi 2-d field reconstruction using the conjoint cylindrical wave expansion,” *IEEE Transactions on Antennas and Propagation*, vol. 57, no. 4, pp. 1095–1104, 2009.

[73] M. C. Wicks, B. Himed, J. Bracken, H. Bascom, and J. Clancy, “Ultra narrow band adaptive tomographic radar,” in *1st IEEE International Workshop on Computational Advances in Multi-Sensor Adaptive Processing, 2005*, pp. 36–39, IEEE, 2005.

[74] K. M. Magde and M. C. Wicks, “Waveforms in virtual tomographic arrays,” in *International Waveform Diversity and Design Conference, 2007.*, pp. 83–87, IEEE, 2007.

[75] C. Chang and A. Sahai, “Object tracking in a 2d uwb sensor network,” in *Thirty-Eighth Asilomar Conference on Signals, Systems and Computers, 2004.*, vol. 1, pp. 1252–1256, IEEE, 2004.

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[76] M. Rydstrom, E. G. Strom, A. Svensson, and L. Reggiani, "An algorithm for positioning relays and point scatterers in wireless systems," *IEEE Signal Processing Letters*, vol. 15, pp. 381–384, 2008.

[77] W. Guo, N. P. Filer, and R. Zetik, "Indoor mapping and positioning using impulse radios," in *Proc. IEEE/ION Position Location and Navigation Symposium (PLANS)*, pp. 153–163, 2006.

[78] R. Thoma, O. Hirsch, J. Sachs, and R. Zetik, "Uwb sensor networks for position location and imaging of objects and environments," in *The Second European Conference on Antennas and Propagation, 2007. EuCAP 2007.*, pp. 1–9, IET, 2007.

[79] J. Wilson and N. Patwari, "Radio tomographic imaging with wireless networks," *IEEE Transactions on Mobile Computing*, vol. 9, no. 5, pp. 621–632, 2010.

[80] M. A. Kanso and M. G. Rabbat, "Compressed rf tomography for wireless sensor networks: Centralized and decentralized approaches," in *International Conference on Distributed Computing in Sensor Systems*, pp. 173–186, Springer, 2009.

[81] A. E. Kosba, A. Saeed, and M. Youssef, "Rasid: A robust wlan device-free passive motion detection system," in *IEEE international conference on Pervasive computing and communications (PerCom), 2012*, pp. 180–189, IEEE, 2012.

[82] J. Wang, Q. Gao, M. Pan, X. Zhang, Y. Yu, and H. Wang, "Toward accurate device-free wireless localization with a saddle surface model," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 8, pp. 6665–6677, 2016.

[83] C. Liu, D. Fang, Z. Yang, H. Jiang, X. Chen, W. Wang, T. Xing, and L. Cai, "Rss distribution-based passive localization and its application in sensor networks," *IEEE Transactions on Wireless Communications*, vol. 15, no. 4, pp. 2883–2895, 2016.

[84] P. Wu, X. Wu, G. Chen, M. Shan, and X. Zhu, "A few bits are enough: Energy efficient device-free localization," *Computer Communications*, vol. 83, pp. 72–80, 2016.

[85] B. Wei, A. Varshney, N. Patwari, W. Hu, T. Voigt, and C. T. Chou, "drti: Directional radio tomographic imaging," in *Proceedings of the 14th International Conference on Information Processing in Sensor Networks*, pp. 166–177, ACM, 2015.

[86] Y. Guo, K. Huang, N. Jiang, X. Guo, Y. Li, and G. Wang, "An exponential-rayleigh model for rss-based device-free localization and tracking," *IEEE transactions on mobile computing*, vol. 14, no. 3, pp. 484–494, 2015.

[87] V. Rampa, S. Savazzi, M. Nicoli, and M. D'Amico, "Physical modeling and performance bounds for device-free localization systems," *IEEE Signal processing letters*, vol. 22, no. 11, pp. 1864–1868, 2015.

[88] D. Zhang, Y. Liu, X. Guo, and L. M. Ni, "Rass: A real-time, accurate, and scalable system for tracking transceiver-free objects," *IEEE Transactions on Parallel and Distributed Systems*, vol. 24, no. 5, pp. 996–1008, 2013.

[89] D. Zhang, K. Lu, R. Mao, Y. Feng, Y. Liu, Z. Ming, and L. M. Ni, "Fine-grained localization for multiple transceiver-free objects by using rf-based technologies," *IEEE Transactions on Parallel and Distributed Systems*, vol. 25, no. 6, pp. 1464–1475, 2014.

[90] J. Wang, H. Jiang, J. Xiong, K. Jamieson, X. Chen, D. Fang, and B. Xie, "Lifs: Low human-effort, device-free localization with fine-grained subcarrier information," 2016.

[91] X. Li, S. Li, D. Zhang, J. Xiong, Y. Wang, and H. Mei, "Dynamic-music: accurate device-free indoor localization," in *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pp. 196–207, ACM, 2016.

[92] J. Wang, D. Fang, X. Chen, Z. Yang, T. Xing, and L. Cai, "Lcs: Compressive sensing based device-free localization for multiple targets in sensor networks," in *Proceedings IEEE INFOCOM, 2013*, pp. 145–149, IEEE, 2013.

[93] L. Chang, X. Chen, Y. Wang, D. Fang, J. Wang, T. Xing, and Z. Tang, "Fitloc: Fine-grained and low-cost device-free localization for multiple targets over various areas," *IEEE/ACM Transactions on Networking*, 2017.

[94] J. Wang, D. Fang, Z. Yang, H. Jiang, X. Chen, T. Xing, and L. Cai, "E-hipa: An energy-efficient framework for high-precision multi-target-adaptive device-free localization," *IEEE Transactions on Mobile Computing*, vol. 16, no. 3, pp. 716–729, 2017.

[95] Y. Zheng and A. Men, "Through-wall tracking with radio tomography networks using foreground detection," in *IEEE Wireless Communications and Networking Conference (WCNC), 2012*, pp. 3278–3283, IEEE, 2012.

[96] Y. Zhao and N. Patwari, "Noise reduction for variance-based device-free localization and tracking," in *8th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON), 2011*, pp. 179–187, IEEE, 2011.

[97] Y. Zhao and N. Patwari, "Robust estimators for variance-based device-free localization and tracking," 2015.

[98] Y. Zhao and N. Patwari, "Histogram distance-based radio tomographic localization," in *Proceedings of the 11th international conference on Information Processing in Sensor Networks*, pp. 129–130, ACM, 2012.

[99] Y. Zhao, N. Patwari, J. M. Phillips, and S. Venkatasubramanian, "Radio tomographic imaging and tracking of stationary and moving people via kernel distance," in *Proceedings of the 12th international conference on Information processing in sensor networks*, pp. 229–240, ACM, 2013.

[100] O. Kaltiokallio, M. Bocca, and N. Patwari, "A fade level-based spatial model for radio tomographic imaging," *IEEE Transactions on Mobile Computing*, vol. 13, no. 6, pp. 1159–1172, 2014.

[101] O. Kaltiokallio, H. Yigitler, and R. Jantti, "A three-state received signal strength model for device-free localization," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 10, pp. 9226–9240, 2017.

[102] Y. Luo, K. Huang, X. Guo, and G. Wang, "A hierarchical rss model for rf-based device-free localization," *Pervasive and Mobile Computing*, vol. 31, pp. 124–136, 2016.

[103] S. Savazzi, M. Nicoli, F. Carminati, and M. Riva, "A bayesian approach to device-free localization: modeling and experimental assessment," *IEEE Journal of Selected Topics in Signal Processing*, vol. 8, no. 1, pp. 16–29, 2014.

[104] Z. Wang, H. Liu, S. Xu, X. Bu, and J. An, "Bayesian device-free localization and tracking in a binary rf sensor network," *Sensors*, vol. 17, no. 5, p. 969, 2017.

[105] S. Huang, B. Song, H. Wang, W. Xiao, and L. Shi, "Gaussian process model enabled particle filter for device-free localization," in *20th International Conference on Information Fusion*, 2017.

[106] S. Nannuru, Y. Li, M. Coates, and B. Yang, "Multi-target device-free tracking using radio frequency tomography," in *Seventh International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP), 2011*, pp. 508–513, IEEE, 2011.

[107] F. Thouin, S. Nannuru, and M. Coates, "Multi-target tracking for measurement models with additive contributions," in *Proceedings of the 14th International Conference on Information Fusion (FUSION), 2011*, pp. 1–8, IEEE, 2011.

[108] S. Nannuru, Y. Li, Y. Zeng, M. Coates, and B. Yang, "Radio-frequency tomography for passive indoor multitarget tracking," *IEEE Transactions on Mobile Computing*, vol. 12, no. 12, pp. 2322–2333, 2013.

[109] J. Wilson and N. Patwari, "A fade-level skew-laplace signal strength model for device-free localization with wireless networks," *IEEE Transactions on Mobile Computing*, vol. 11, no. 6, pp. 947–958, 2012.

[110] C. Xu, B. Firner, R. S. Moore, Y. Zhang, W. Trappe, R. Howard, F. Zhang, and N. An, "Scpl: Indoor device-free multi-subject counting and localization using radio signal strength," in *ACM/IEEE International Conference on Information Processing in Sensor Networks (IPSN), 2013*, pp. 79–90, IEEE, 2013.

[111] C. Xu, "Device-free people counting and localization," in *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication*, pp. 367–372, ACM, 2013.

[112] J. Zhang, W. Xiao, S. Zhang, and S. Huang, "Device-free localization via an extreme learning machine with parameterized geometrical feature extraction," *Sensors*, vol. 17, no. 4, p. 879, 2017.

[113] Q. Lei, H. Zhang, H. Sun, and L. Tang, "Fingerprint-based device-free localization in changing environments using enhanced channel selection and logistic regression," *IEEE Access*, 2017.

[114] S. Kianoush, S. Savazzi, F. Vicentini, V. Rampa, and M. Giussani, "Device-free rf human body fall detection and localization in industrial workplaces," *IEEE Internet of Things Journal*, vol. 4, no. 2, pp. 351–362, 2017.

[115] C. Xu, B. Firner, Y. Zhang, and R. E. Howard, "The case for efficient and robust rf-based device-free localization," *IEEE Transactions on Mobile Computing*, vol. 15, no. 9, pp. 2362–2375, 2016.

[116] L. Chang, J. Xiong, Y. Wang, X. Chen, J. Hu, and D. Fang, "iupdater: Low cost rss fingerprints updating for device-free localization," in *37th International Conference on Distributed Computing Systems (ICDCS), 2017 IEEE*, pp. 900–910, IEEE, 2017.

[117] Y. Shu, Y. Huang, J. Zhang, P. Coué, P. Cheng, J. Chen, and K. G. Shin, "Gradient-based fingerprinting for indoor localization and tracking," *IEEE Transactions on Industrial Electronics*, vol. 63, no. 4, pp. 2424–2433, 2016.

[118] R. Zhou, X. Lu, P. Zhao, and J. Chen, "Device-free presence detection and localization with svm and csi fingerprinting," *IEEE Sensors Journal*, vol. 17, no. 23, pp. 7990–7999, 2017.

[119] M. Bocca, O. Kaltiokallio, N. Patwari, and S. Venkatasubramanian, "Multiple target tracking with rf sensor networks," *IEEE Transactions on Mobile Computing*, vol. 13, no. 8, pp. 1787–1800, 2014.

[120] I. Sabek, M. Youssef, and A. V. Vasilakos, "Ace: An accurate and efficient multi-entity device-free wlan localization system," *IEEE transactions on mobile computing*, vol. 14, no. 2, pp. 261–273, 2015.

[121] J. Wang, X. Zhang, Q. Gao, H. Yue, and H. Wang, "Device-free wireless localization and activity recognition: A deep learning approach," *IEEE Transactions on Vehicular Technology*, 2016.

[122] X. Li, S. Ding, Z. Li, and B. Tan, "Device-free localization via dictionary learning with difference of convex programming," *IEEE Sensors Journal*, vol. 17, no. 17, pp. 5599–5608, 2017.

[123] F. Adib and D. Katabi, *See through walls with WiFi!*, vol. 43. ACM, 2013.

[124] K. R. Joshi, D. Bharadia, M. Kotaru, and S. Katti, "Wideo: Fine-grained device-free motion tracing using rf backscatter.," in *NSDI*, pp. 189–204, 2015.

[125] L. Yang, Q. Lin, X. Li, T. Liu, and Y. Liu, "See through walls with cots rfid system!," in *Proceedings of the 21st Annual International Conference on Mobile Computing and Networking*, pp. 487–499, ACM, 2015.

[126] Y. Kilic, H. Wymeersch, A. Meijerink, M. J. Bentum, and W. G. Scanlon, "Device-free person detection and ranging in uwb networks," *IEEE journal of selected topics in signal processing*, vol. 8, no. 1, pp. 43–54, 2014.

[127] T. Wei and X. Zhang, "mtrack: High-precision passive tracking using millimeter wave radios," in *Proceedings of the 21st Annual International Conference on Mobile Computing and Networking*, pp. 117–129, ACM, 2015.

[128] T. W. Hnat, E. Griffiths, R. Dawson, and K. Whitehouse, "Doorjamb: unobtrusive room-level tracking of people in homes using doorway sensors," in *Proceedings of the 10th ACM Conference on Embedded Network Sensor Systems*, pp. 309–322, ACM, 2012.

[129] J. Wang, J. Xiong, H. Jiang, X. Chen, and D. Fang, "D-watch: Embracing "bad" multipaths for device-free localization with cots rfid devices," *IEEE/ACM Transactions on Networking*, vol. 25, no. 6, pp. 3559–3572, 2017.

[130] Q. Z. S. W. Ruan, N. F. L. Yao, X. Li, and L. Yang, "Device-free human localization and tracking with uhf passive rfid tags: A data-driven approach," *Journal of Network and Computer Applications*, 2018.

[131] S. Bartoletti, A. Conti, and M. Z. Win, "Device-free counting via wideband signals," *IEEE Journal on Selected Areas in Communications*, vol. 35, no. 5, pp. 1163–1174, 2017.

[132] M. Z. Win and R. A. Scholtz, "Impulse radio: How it works," *IEEE Communications letters*, vol. 2, no. 2, pp. 36–38, 1998.

[133] M. Z. Win and R. A. Scholtz, "Ultra-wide bandwidth time-hopping spread-spectrum impulse radio for wireless multiple-access communications," *IEEE Transactions on communications*, vol. 48, no. 4, pp. 679–689, 2000.

[134] L. Yang and G. B. Giannakis, "Ultra-wideband communications: an idea whose time has come," *IEEE signal processing magazine*, vol. 21, no. 6, pp. 26–54, 2004.

[135] S. Bartoletti, W. Dai, A. Conti, and M. Z. Win, "A mathematical model for wideband ranging," *IEEE Journal of Selected Topics in Signal Processing*, vol. 9, no. 2, pp. 216–228, 2015.

[136] S. Bartoletti, A. Giorgetti, M. Z. Win, and A. Conti, "Blind selection of representative observations for sensor radar networks," *IEEE Transactions on Vehicular Technology*, vol. 64, no. 4, pp. 1388–1400, 2015.

[137] Y. Shen, S. Mazuelas, and M. Z. Win, "Network navigation: Theory and interpretation," *IEEE Journal on Selected Areas in Communications*, vol. 30, no. 9, pp. 1823–1834, 2012.

[138] X. Quan, J. W. Choi, and S. H. Cho, "In-bound/out-bound detection of people's movements using an ir-uwb radar system," in *International Conference on Electronics, Information and Communications (ICEIC), 2014*, pp. 1–2, IEEE, 2014.

[139] J. W. Choi, J. H. Kim, and S. H. Cho, "A counting algorithm for multiple objects using an ir-uwb radar system," in *3rd IEEE International Conference on Network Infrastructure and Digital Content (IC-NIDC), 2012*, pp. 591–595, IEEE, 2012.

[140] J. He and A. Arora, "A regression-based radar-mote system for people counting," in *2014 IEEE International Conference on Pervasive Computing and Communications (PerCom)*, pp. 95–102, IEEE, 2014.

[141] M. Bocca, O. Kaltiokallio, and N. Patwari, "Radio tomographic imaging for ambient assisted living," in *International Competition on Evaluating AAL Systems through Competitive Benchmarking*, pp. 108–130, Springer, 2012.

[142] M. S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, "A tutorial on particle filters for online nonlinear/non-gaussian bayesian tracking," *IEEE Transactions on signal processing*, vol. 50, no. 2, pp. 174–188, 2002.

[143] R. R. Yager, "Intelligent control of the hierarchical agglomerative clustering process," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 30, no. 6, pp. 835–845, 2000.

[144] P. Closas and M. F. Bugallo, "Improving accuracy by iterated multiple particle filtering," *IEEE Signal Processing Letters*, vol. 19, no. 8, pp. 531–534, 2012.

[145] H. Mokhtari and P. Lazaridis, "Comparative study of lateral profile knife-edge diffraction and ray tracing technique using gtd in urban environment," *IEEE Transactions on Vehicular Technology*, vol. 48, no. 1, pp. 255–261, 1999.

[146] L. Qiu, W. Wang, T. Jin, B. Lu, and Z. Zhou, "The crlb analysis for target localization behind wall and in free space," in *2017 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC)*, pp. 1–5, IEEE, 2017.

[147] D. Zhang, J. Ma, Q. Chen, and L. M. Ni, "An rf-based system for tracking transceiver-free objects," in *Fifth Annual IEEE International Conference on Pervasive Computing and Communications, 2007. PerCom'07.*, pp. 135–144, IEEE, 2007.

[148] D. Zhang and L. M. Ni, "Dynamic clustering for tracking multiple transceiver-free objects," in *IEEE International Conference on Pervasive Computing and Communications, 2009. PerCom 2009.*, pp. 1–8, IEEE, 2009.

[149] S. Sen, R. R. Choudhury, B. Radunovic, and T. Minka, "Precise indoor localization using phy layer information," in *Proceedings of the 10th ACM Workshop on hot topics in networks*, p. 18, ACM, 2011.

[150] Z. Zhou, Z. Yang, C. Wu, L. Shangguan, and Y. Liu, "Omnidirectional coverage for device-free passive human detection," *IEEE Transactions on Parallel and Distributed Systems*, vol. 25, no. 7, pp. 1819–1829, 2014.

[151] R. Ravichandran, E. Saba, K.-Y. Chen, M. Goel, S. Gupta, and S. N. Patel, "Wibreathe: Estimating respiration rate using wireless signals in natural settings in the home," in *IEEE International Conference on Pervasive Computing and Communications (PerCom), 2015*, pp. 131–139, IEEE, 2015.

[152] Z. Zhou, Z. Yang, C. Wu, Y. Liu, and L. M. Ni, "On multipath link characterization and adaptation for device-free human detection," in *IEEE 35th International Conference on Distributed Computing Systems (ICDCS), 2015*, pp. 389–398, IEEE, 2015.

[153] H. Wang, D. Zhang, J. Ma, Y. Wang, Y. Wang, D. Wu, T. Gu, and B. Xie, "Human respiration detection with commodity wifi devices: do user location and body orientation matter?," in *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pp. 25–36, ACM, 2016.

[154] S. Palipana, P. Agrawal, and D. Pesch, "Channel state information based human presence detection using non-linear techniques.," in *BuildSys SenSys*, pp. 177–186, 2016.

[155] S. Depatla, A. Muralidharan, and Y. Mostofi, "Occupancy estimation using only wifi power measurements," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 7, pp. 1381–1393, 2015.

[156] W. Wang, A. X. Liu, M. Shahzad, K. Ling, and S. Lu, "Understanding and modeling of wifi signal based human activity recognition," in *Proceedings of the 21st annual international conference on mobile computing and networking*, pp. 65–76, ACM, 2015.

[157] Q. Pu, S. Gupta, S. Gollakota, and S. Patel, "Whole-home gesture recognition using wireless signals," in *Proceedings of the 19th annual international conference on Mobile computing & networking*, pp. 27–38, ACM, 2013.

[158] T. Xing, D. Fang, X. Chen, M. Jin, X. Zheng, and K. Zhao, "Doppler effect based moving target detection adaptive to speed," in *Proceedings of the 1st Workshop on Context Sensing and Activity Recognition*, pp. 41–46, ACM, 2015.

[159] J. Xiong and K. Jamieson, "Arraytrack: A fine-grained indoor location system," Usenix, 2013.

[160] S. Sen, J. Lee, K.-H. Kim, and P. Congdon, "Avoiding multipath to revive inbuilding wifi localization," in *Proceeding of the 11th annual international conference on Mobile systems, applications, and services*, pp. 249–262, ACM, 2013.

[161] C. Zhang, F. Li, J. Luo, and Y. He, "ilocscan: Harnessing multipath for simultaneous indoor source localization and space scanning," in *Proceedings of the 12th ACM Conference on Embedded Network Sensor Systems*, pp. 91–104, ACM, 2014.

[162] D. Vasisht, S. Kumar, and D. Katabi, "Decimeter-level localization with a single wifi access point.," in *NSDI*, pp. 165–178, 2016.

[163] S. Sigg, M. Scholz, S. Shi, Y. Ji, and M. Beigl, "Rf-sensing of activities from non-cooperative subjects in device-free recognition systems using ambient and local signals," *IEEE Transactions on Mobile Computing*, vol. 13, no. 4, pp. 907–920, 2014.

[164] M. McCracken, M. Bocca, and N. Patwari, "Joint ultra-wideband and signal strength-based through-building tracking for tactical operations," in *10th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON), 2013*, pp. 309–317, IEEE, 2013.

[165] C.-P. Wang and B. Jo, "Applications of a kullback-leibler divergence for comparing non-nested models," *Statistical modelling*, vol. 13, no. 5-6, pp. 409–429, 2013.

[166] P. Bahl and V. N. Padmanabhan, "Radar: An in-building rf-based user location and tracking system," in *Proceedings. IEEE Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. INFOCOM 2000*, vol. 2, pp. 775–784, Ieee, 2000.

[167] P. Bahl, V. N. Padmanabhan, and A. Balachandran, "Enhancements to the radar user location and tracking system," *Microsoft Research*, vol. 2, no. MSR-TR-2000-12, pp. 775–784, 2000.

[168] M. Youssef and A. Agrawala, "The horus location determination system," *Wireless Networks*, vol. 14, no. 3, pp. 357–374, 2008.

[169] J. Wang, Q. Gao, Y. Yu, P. Cheng, L. Wu, and H. Wang, "Robust device-free wireless localization based on differential rss measurements," *IEEE transactions on industrial electronics*, vol. 60, no. 12, pp. 5943–5952, 2013.

[170] Y. Li, X. Chen, M. Coates, and B. Yang, "Sequential monte carlo radio-frequency tomographic tracking," in *2011 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 3976–3979, IEEE, 2011.

[171] X. Chen, A. Edelstein, Y. Li, M. Coates, M. Rabbat, and A. Men, "Sequential monte carlo for simultaneous passive device-free tracking and sensor localization using received signal strength measurements," in *2011 10th International Conference on Information Processing in Sensor Networks (IPSN)*, pp. 342–353, IEEE, 2011.

[172] Z. Wang, H. Liu, S. Xu, X. Bu, and J. An, "A diffraction measurement model and particle filter tracking method for rss-based dfl," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 11, pp. 2391–2403, 2015.

[173] G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew, "Extreme learning machine: theory and applications," *Neurocomputing*, vol. 70, no. 1-3, pp. 489–501, 2006.

[174] Y.-Y. Chiang, W.-H. Hsu, S.-C. Yeh, Y.-C. Li, and J.-S. Wu, "Fuzzy support vector machines for device-free localization," in *2012 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*, pp. 2169–2172, IEEE, 2012.

[175] G.-B. Huang, H. Zhou, X. Ding, and R. Zhang, "Extreme learning machine for regression and multiclass classification," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 42, no. 2, pp. 513–529, 2012.

[176] G. Huang, G.-B. Huang, S. Song, and K. You, "Trends in extreme learning machines: A review," *Neural Networks*, vol. 61, pp. 32–48, 2015.

[177] W. Xiao, J. Zhang, Y. Li, S. Zhang, and W. Yang, "Class-specific cost regulation extreme learning machine for imbalanced classification," *Neurocomputing*, vol. 261, pp. 70–82, 2017.

[178] W. Zong and G.-B. Huang, "Face recognition based on extreme learning machine," *Neurocomputing*, vol. 74, no. 16, pp. 2541–2551, 2011.

[179] A. A. Mohammed, R. Minhas, Q. J. Wu, and M. A. Sid-Ahmed, "Human face recognition based on multidimensional pca and extreme learning machine," *Pattern Recognition*, vol. 44, no. 10-11, pp. 2588–2597, 2011.

[180] H. Zhang, Y. Yin, and S. Zhang, "An improved elm algorithm for the measurement of hot metal temperature in blast furnace," *Neurocomputing*, vol. 174, pp. 232–237, 2016.

[181] S. Zhang, X. Chen, and Y. Yin, "An elm based online soft sensing approach for alumina concentration detection," *Mathematical Problems in Engineering*, vol. 2015, 2015.

[182] W. Xiao and Y. Lu, "Daily human physical activity recognition based on kernel discriminant analysis and extreme learning machine," *Mathematical Problems in Engineering*, vol. 2015, pp. 1–8, 2015.

[183] R. Minhas, A. Baradarani, S. Seifzadeh, and Q. J. Wu, "Human action recognition using extreme learning machine based on visual vocabularies," *Neurocomputing*, vol. 73, no. 10-12, pp. 1906–1917, 2010.

[184] J. Cao, Y. Zhao, X. Lai, M. E. H. Ong, C. Yin, Z. X. Koh, and N. Liu, "Landmark recognition with sparse representation classification and extreme learning machine," *Journal of the Franklin Institute*, vol. 352, no. 10, pp. 4528–4545, 2015.

[185] J. Cao, T. Chen, and J. Fan, "Landmark recognition with compact bow histogram and ensemble elm," *Multimedia Tools and Applications*, vol. 75, no. 5, pp. 2839–2857, 2016.

[186] C. Pan, D. S. Park, Y. Yang, and H. M. Yoo, "Leukocyte image segmentation by visual attention and extreme learning machine," *Neural Computing and Applications*, vol. 21, no. 6, pp. 1217–1227, 2012.

[187] B. Mager, *Maintaining accuracy of device-free localization systems in changing environments*. The University of Utah, 2014.

[188] B. Mager, P. Lundrigan, and N. Patwari, "Fingerprint-based device-free localization performance in changing environments," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 11, pp. 2429–2438, 2015.

[189] M. Youssef and A. Agrawala, "The horus wlan location determination system," in *Proceedings of the 3rd international conference on Mobile systems, applications and services*, pp. 205–218, ACM, 2005.

[190] A. Rai, K. K. Chintalapudi, V. N. Padmanabhan, and R. Sen, "Zee: Zero-effort crowdsourcing for indoor localization," in *Proceedings of the 18th annual international conference on Mobile computing and networking*, pp. 293–304, ACM, 2012.

[191] K. Chintalapudi, A. Padmanabha Iyer, and V. N. Padmanabhan, "Indoor localization without the pain," in *Proceedings of the sixteenth annual international conference on Mobile computing and networking*, pp. 173–184, ACM, 2010.

[192] Z. Yang, C. Wu, and Y. Liu, "Locating in fingerprint space: wireless indoor localization with little human intervention," in *Proceedings of the 18th annual international conference on Mobile computing and networking*, pp. 269–280, ACM, 2012.

[193] R. Zhou, J. Chen, X. Lu, and J. Wu, "Csi fingerprinting with svm regression to achieve device-free passive localization," in *2017 IEEE 18th International Symposium on A World of Wireless, Mobile and Multimedia Networks (WoWMoM)*, pp. 1–9, IEEE, 2017.

[194] C. Vonesch, T. Blu, and M. Unser, "Generalized daubechies wavelet families," *IEEE Transactions on Signal Processing*, vol. 55, no. 9, pp. 4415–4429, 2007.

[195] D. Heckerman and C. Meek, "Models and selection criteria for regression and classification," in *Proceedings of the Thirteenth conference on Uncertainty in artificial intelligence*, pp. 223–228, Morgan Kaufmann Publishers Inc., 1997.

[196] J. Xiao, K. Wu, Y. Yi, L. Wang, and L. M. Ni, "Fimd: Fine-grained device-free motion detection," in *18th International Conference on Parallel and Distributed Systems (ICPADS), 2012 IEEE*, pp. 229–235, IEEE, 2012.

[197] J. Xiao, K. Wu, Y. Yi, L. Wang, and L. M. Ni, "Pilot: Passive device-free indoor localization using channel state information," in *IEEE 33rd international conference on Distributed computing systems (ICDCS), 2013*, pp. 236–245, IEEE, 2013.

[198] Z. Zhou, Z. Yang, C. Wu, L. Shangguan, and Y. Liu, "Towards omnidirectional passive human detection," in *Proceedings IEEE INFOCOM, 2013*, pp. 3057–3065, IEEE, 2013.

[199] C. Wu, Z. Yang, Z. Zhou, X. Liu, Y. Liu, and J. Cao, "Non-invasive detection of moving and stationary human with wifi," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 11, pp. 2329–2342, 2015.

[200] S. C. Carey and W. R. Scott, "Software defined radio for stepped-frequency, ground-penetrating radar," in *2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, pp. 4825–4828, IEEE, 2017.

[201] G. Lu, Y. Yan, A. Kolagunda, and C. Kambhamettu, "A fast 3d indoor-localization approach based on video queries," in *International Conference on Multimedia Modeling*, pp. 218–230, Springer, 2016.

[202] H. Wang, S. Sen, A. Mariakakis, A. Elgohary, M. Farid, M. Youssef, and R. Roy Choudhury, "Video: Unsupervised indoor localization (unloc): Beyond the prototype," in *Proceedings of the 12th annual international conference on Mobile systems, applications, and services*, pp. 393–393, ACM, 2014.

[203] R. S. Moore, R. Howard, P. Kuksa, and R. P. Martin, "A geometric approach to device-free motion localization using signal strength," *Technical Report, Rutgers University*, 2010.

[204] S. Shi, S. Sigg, and Y. Ji, "Passive detection of situations from ambient fm-radio signals," in *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*, pp. 1049–1053, ACM, 2012.

[205] A. Yarovoy, L. Ligthart, J. Matuzas, and B. Levitas, "Uwb radar for human being detection," *IEEE Aerospace and Electronic Systems Magazine*, vol. 21, no. 3, pp. 10–14, 2006.

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[206] S. Chang, N. Mitsumoto, and J. W. Burdick, "An algorithm for uwb radar-based human detection," in *IEEE Radar Conference, 2009*, pp. 1–6, IEEE, 2009.

[207] S. Chang, R. Sharan, M. Wolf, N. Mitsumoto, and J. W. Burdick, "Uwb radar-based human target tracking," in *IEEE Radar Conference, 2009*, pp. 1–6, IEEE, 2009.

[208] S. Chang, M. Wolf, and J. W. Burdick, "Human detection and tracking via ultra-wideband (uwb) radar," in *IEEE International Conference on Robotics and Automation (ICRA), 2010*, pp. 452–457, IEEE, 2010.

[209] Y. Kilic, H. Wymeersch, A. Meijerink, M. J. Bentum, and W. G. Scanlon, "An experimental study of uwb device-free person detection and ranging," in *IEEE International Conference on Ultra-Wideband (ICUWB), 2013*, pp. 43–48, IEEE, 2013.

[210] K. Qian, C. Wu, Z. Zhou, Y. Zheng, Z. Yang, and Y. Liu, "Inferring motion direction using commodity wi-fi for interactive exergames," in *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pp. 1961–1972, ACM, 2017.

[211] W. Wang, A. X. Liu, and M. Shahzad, "Gait recognition using wifi signals," in *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pp. 363–373, ACM, 2016.

[212] D. Puthal, S. P. Mohanty, S. A. Bhavake, G. Morgan, and R. Ranjan, "Fog computing security challenges and future directions [energy and security]," *IEEE Consumer Electronics Magazine*, vol. 8, no. 3, pp. 92–96, 2019.

[213] D. Puthal, S. P. Mohanty, P. Nanda, and U. Choppali, "Building security perimeters to protect network systems against cyber threats [future directions]," *IEEE Consumer Electronics Magazine*, vol. 6, no. 4, pp. 24–27, 2017.

[214] Y. Qiao, O. Zhang, W. Zhou, K. Srinivasan, and A. Arora, "Phycloak: Obfuscating sensing from communication signals.," in *USENIX Annual Technical Conference*, 2016.

[215] C. Alippi, M. Bocca, G. Boracchi, N. Patwari, and M. Roveri, "Rti goes wild: Radio tomographic imaging for outdoor people detection and localization," *IEEE Transactions on Mobile Computing*, vol. 15, no. 10, pp. 2585–2598, 2016.

[216] D. Maas, J. Wilson, and N. Patwari, "Toward a rapidly deployable radio tomographic imaging system for tactical operations," in *IEEE 38th Conference on Local Computer Networks Workshops (LCN Workshops), 2013*, pp. 203–210, IEEE, 2013.

[217] Y. Zeng, P. H. Pathak, and P. Mohapatra, "Wiwho: wifi-based person identification in smart spaces," in *Proceedings of the 15th International Conference on Information Processing in Sensor Networks*, p. 4, IEEE Press, 2016.

[218] F. Hong, X. Wang, Y. Yang, Y. Zong, Y. Zhang, and Z. Guo, "Wfid: Passive device-free human identification using wifi signal," in *Proceedings of the 13th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services*, pp. 47–56, ACM, 2016.

[219] W. Xi, J. Zhao, X.-Y. Li, K. Zhao, S. Tang, X. Liu, and Z. Jiang, "Electronic frog eye: Counting crowd using wifi," in *proceedings ieee Infocom, 2014*, pp. 361–369, IEEE, 2014.

[220] S. Di Domenico, G. Pecoraro, E. Cianca, and M. De Sanctis, "Trained-once device-free crowd counting and occupancy estimation using wifi: A doppler spectrum based approach," in *IEEE 12th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob), 2016*, pp. 1–8, IEEE, 2016.

[221] R. Edirisinghe, H. Lingard, N. Blismas, D. Dias, and R. Wakefield, "Device-free detection to improve construction work health and safety," in *Computing in Civil and Building Engineering (2014)*, pp. 1078–1085, 2014.

[222] X. Zheng, J. Wang, L. Shangguan, Z. Zhou, and Y. Liu, "Smokey: Ubiquitous smoking detection with commercial wifi infrastructures," in *The 35th Annual IEEE International Conference on Computer Communications, IEEE INFOCOM 2016*, pp. 1–9, IEEE, 2016.

[223] N. D. Lane and P. Georgiev, "Can deep learning revolutionize mobile sensing?," in *Proceedings of the 16th International Workshop on Mobile Computing Systems and Applications*, pp. 117–122, ACM, 2015.

[224] X. Li, Y. Zhang, I. Marsic, A. Sarcevic, and R. S. Burd, "Deep learning for rfid-based activity recognition," in *Proceedings of the 14th ACM Conference on Embedded Network Sensor Systems*, pp. 164–175, ACM, 2016.

[225] C. Fischer and H. Gellersen, "Location and navigation support for emergency responders: A survey," *IEEE Pervasive Computing*, vol. 9, no. 1, pp. 38–47, 2010.

[226] S. Tan and J. Yang, "Wifinger: leveraging commodity wifi for fine-grained finger gesture recognition," in *Proceedings of the 17th ACM International Symposium on Mobile Ad Hoc Networking and Computing*, pp. 201–210, ACM, 2016.

[227] G. Wang, Y. Zou, Z. Zhou, K. Wu, and L. M. Ni, "We can hear you with wi-fi!," *IEEE Transactions on Mobile Computing*, vol. 15, no. 11, pp. 2907–2920, 2016.

[228] Y. Wang, X. Jiang, R. Cao, and X. Wang, "Robust indoor human activity recognition using wireless signals," *Sensors*, vol. 15, no. 7, pp. 17195–17208, 2015.

[229] Y. Wang, J. Liu, Y. Chen, M. Gruteser, J. Yang, and H. Liu, "E-eyes: device-free location-oriented activity identification using fine-grained wifi signatures," in *Proceedings of the 20th annual international conference on Mobile computing and networking*, pp. 617–628, ACM, 2014.

[230] Y. Zeng, P. H. Pathak, and P. Mohapatra, "Analyzing shopper's behavior through wifi signals," in *Proceedings of the 2nd workshop on Workshop on Physical Analytics*, pp. 13–18, ACM, 2015.

[231] K. Ali, A. X. Liu, W. Wang, and M. Shahzad, "Keystroke recognition using wifi signals," in *Proceedings of the 21st Annual International Conference on Mobile Computing and Networking*, pp. 90–102, ACM, 2015.

[232] A. Luong, T. Schmid, and N. Patwari, "Demo abstract: A platform enabling local oscillator frequency synchronization," in *14th ACM Conference on Embedded Networked Sensor Systems, SenSys 2016*, Association for Computing Machinery, Inc, 2016.

[233] G. Wang, J.-M. Munoz-Ferreras, C. Gu, C. Li, and R. Gomez-Garcia, "Application of linear-frequency-modulated continuous-wave (lfmcw) radars for tracking of vital signs," *IEEE Transactions on Microwave Theory and Techniques*, vol. 62, no. 6, pp. 1387–1399, 2014.

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