HUMAN ACTIVITY RECOGNITION BASED ON DEVICE-FREE WI-FI SENSING: A COMPREHENSIVE REVIEW

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ABSTRACT

Within the context of the current era's research and advancement in technology, in recent years, the Internet of Things (IoT) has been consistent in the development of applications in several fields like smart cities, smart homes, smart grids, smart agriculture, and so on. Most of the existing research in human activity recognition relies on vision-based, wearable devices, object-tagged, and sensor-based approaches. Despite the superior performance of these approaches, a number of issues have arisen related to the invasion of privacy, light dependency, cost effectiveness, and feasibility. Moreover, these approaches require domain knowledge of different tasks, which may make them complicated for practical deployment. Wi-Fi technology, on the other hand, offers robust possibilities in indoor and outdoor environments for recognizing applications and, combined with a few significant features, makes it a far more attractive option compared to other sensing technologies. Hence, the device-free Wi-Fi-sensing approach is more practical in the smart home environment as it does not require the targeted human to have any device for day-to-day activities. This article's contributions can be summarized as, first, providing primary knowledge on a wireless LAN, the Wi-Fi sensing model; second, sharing the findings of the comprehensive survey scrutinizing the latest developments in human activity or gesture recognition systems based on device-free Wi-Fi sensing systems; third, sharing the analysis of the limitations and key research challenges that need to be addressed in order to expand the device-free Wi-Fi sensing system; and lastly, a discussion and future directions of existing device-free Wi-Fi sensing techniques.

Keywords: Device-free Wi-Fi sensing; Human activity recognition; Internet of Things; Smart home.

1.0 INTRODUCTION

Automatic detection of human activity has been a constant research area in the field of computer vision [1, 2, 79–82]. Therefore, various sectors such as health care, communications, agriculture, homes, cities, and business utilize the many applications that smart and emerging technology in the world delivers. The rapidly growing number of Internet-connected physical devices has accelerated the development of Human Activity Recognition (HAR) applications [3–7, 79–82], and it has established an ecosystem that connects various smart systems to provide precise performance in every task [2], thereby enhancing the quality of human life [3]. Undeniably, HAR-based applications will play a vital role in human activities, systems, and processes. HAR is a highly dynamic and challenging research field that plays a crucial role in diverse applications in a smart home environment [8]. HAR is a technique for recognizing a sequence of data obtained from IoT sensors triggered by actions performed by humans who live in smart homes. Researchers have conducted substantial research on HAR using wearable devices, vision-based, object-tagged, and sensor-based approaches [8, 9, 10].

Although HAR displays a higher performance when these approaches are applied, a number of problems have arisen that are associated with cost effectiveness, light dependency (especially at night, as traditional cameras fail to work if there is no appropriate light), and invasion of privacy. Practicality concerns are also a potential problem. Moreover, it requires domain knowledge for different tasks and is complicated for practical deployment [10]. Hence, concerns about the high-cost, complex computation, feasibility, privacy, security, energy, and storage issues in camera-based, wearable devices, multimedia sensors, and/or tagged sensors must be considered. Since sensor technology has come a long way and is now very cheap, the Wi-Fi-sensing, device-free approach is much easier to use. As a result, most researchers have switched to this method, which uses environment-tagged or dense sensing and wireless signals that can pass through any object [11–12]. Furthermore, this method does not require the targeted human to carry a device or wear any tags during their daily activities, as it utilizes various appropriate sensors to capture their activities in real-time. Table 1 illustrates some key approaches, their advantages, and their limitations for device-bound and device-free approaches. The HAR system could support elderly people or individuals by monitoring their daily activity patterns and intervening in cases of behavioral changes [13-14] [79-83]. Many sensing systems, or wearable devices, have become available on the market in recent years with the promise of improving quality of life. Wearables have the potential to sense and collect physiological data, allowing them to provide services such as mental and physical health monitoring [81].

Generally, people use the appropriate cameras to identify their daily activities, such as sitting, walking, sleeping, cooking, and watching TV [15–18]. However, this raises privacy concerns [19], as patients and the elderly feel uncomfortable wearing these devices all the time. Models are introducing wearables with environmental sensors to capture body movement, aiming to reduce privacy concerns [20, 21, 80–82]. Nevertheless, the models have a more intrusive setup and are more complex. On the other hand, because wearable activity trackers are less obtrusive and can identify variations in physical activity, people often prefer them [22, 81].

Table 1: Summary of Device-Required and Device-Free Approaches in Smart Homes

Categories	Approach	Advantages	Limitations / Challenges
Device-bound	Vision or Camera based	High accuracy	Privacy, security, high cost, complex computation, light conditions, cannot penetrate a wall
	Wearable device based	Reasonable cost	It is not feasible to constantly carry tags, particularly for the elderly or patients who resist wearing them.
	Sensor based	High accuracy	Privacy issue, high cost
	Smart phone	High accuracy	Need to have a smartphone
	Object tag	High accuracy, low-cost	Not feasible, environmental interference, and data noise
Device-free	Wi-fi	Robust, unobtrusive	Dat noise, and environmental interference

Hakan Yekta Yatbaz et al. (2019) assert that detecting human activity requires high accuracy and efficient computation time due to its direct connection to human life. HAR has been considered a primary technological innovation that can enable diversity of application. Nonetheless, the exact identification and recognition of human activity is still a major issue that fascinates many researchers and has triggered a lot of research endeavors. Also, new improvements in Wi-Fi technology using IoT sensors or other methods like deep neural networks, Received Signal Strength (RSS), Channel State Information (CSI), and others make it possible to track human activities without using any devices or being intrusive [23]. Yet, it remains a considerably challenging research area, mainly due to intra-class dissimilarity in the visual appearance of human activities [1]. We structure the remaining part of the article as follows:

Section II delves into the fundamental understanding of wireless LANs and Wi-Fi sensing environments. Section III provides a comprehensive survey of device-free HAR methods used in Wi-Fi sensing environments. Section IV provides an analysis of the limitations and key research challenges; Section V provides a discussion and future endeavors in a device-free Wi-Fi sensing environment.

2.0 PRIMARY KNOWLEDGE ON WIRELESS LAN, WI-FI SENSING

According to IEEE, wireless LAN and Wi-Fi are based on the IEEE 802.11 family of wireless network protocols or standards, and this exists in some protocols, namely 802.11a, 802.11b, 802.11g, 802.11ac, and 802.11n [24]. These protocols vary in relation to channel size and data throughput [24, 25].

2.1 Wireless LAN

Tony Xiao Han et al. (2020) typically use 802.11bf standards for wireless local area network (WLAN) device detection and internet access. While devices operating in unlicensed bands do not require formal authorization, users must adhere to local government regulations while using these bands, according to CISCO regulatory domains. The WLAN devices used in these domains must adhere to the specifications of the relevant regulatory domain, taking into account the conditions of the regulatory domain in various parts of the world. The regulatory organizations do set certain measures for the standard, though the requirements do not influence the interoperability of IEEE 802.11b/g and 802.11a products [26]. According to Christensson (2020), devices in a conventional wired LAN connect and communicate over ethernet cables, transmitting data in a series of ethernet packets over physical cables. On the other hand, wireless LAN enables devices to connect and communicate wirelessly through Wi-Fi, transmitting data packets over the air. Nevertheless, both function in a similar way. Wireless routers serve as a base station and provide Internet access to connected devices through an attached modem (modulation and de-modulation) or other Wi-Fi-enabled devices such as tablets, smartphones, laptops, smart home controllers, smart appliances, etc., within range of the router's wireless signal [27, 30]. A WLAN accounted for the wireless association between correspondence terminals [27–28]. A router and an access point (AP) would allow these terminals to access the Internet, as indicated in the wireless LAN ecosystem diagram (Fig. 1). The wireless adapter device translates data into a radio signal, which the wireless router receives, decodes, and relays to the internet using its physical Ethernet connection [29].

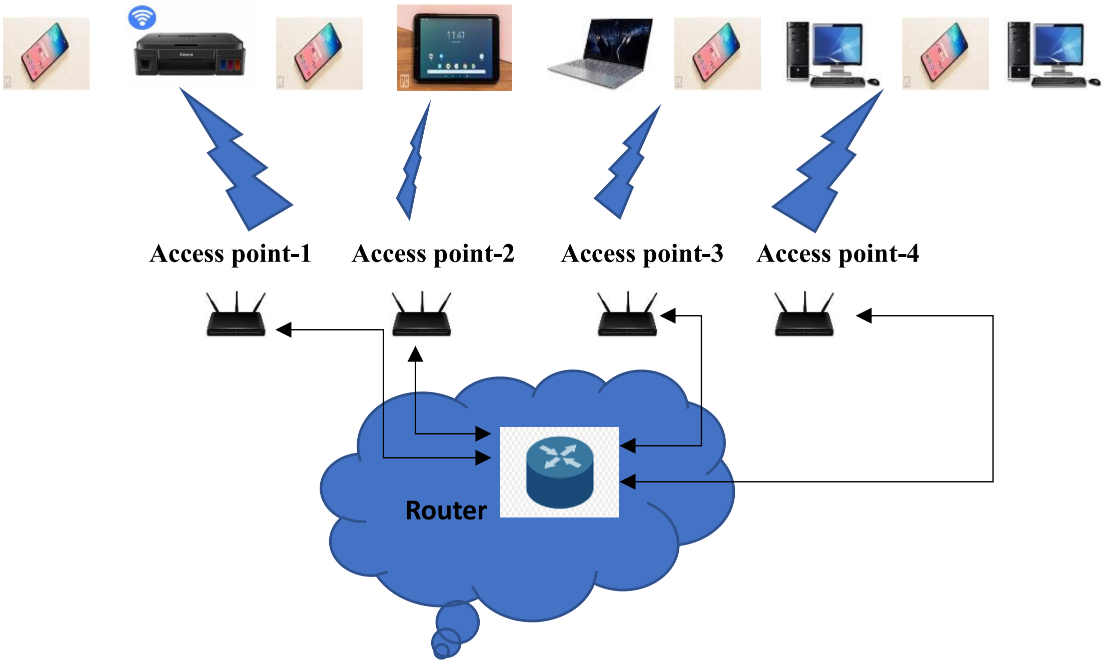

Fig. 1. A typical ecosystem of Wireless LAN

2.2 Wi-Fi Sensing

The Wi-Fi sensing system is one of the ubiquitous wireless communications technologies that can be active or passive and communicate in either an infrastructure or ad hoc mode. In the ad-hoc mode, each system directly communicates with each other, while in the infrastructure mode, all modes communicate through a central Wi-Fi access point (AP) [31]. Fig. 2 illustrates a typical passive Wi-Fi sensing system, which provides connectivity and network services with minimal processing overhead and aids in security and family care services such as human activity detection, recognition, and vital sign detection in smart home and IoT applications [32, 79-85]. Moreover, building a dedicated sensing network that measures based on signal interaction and movement requires additional gateways or other sensors.

By pinging the Wi-Fi environment, these systems can easily track the locations of humans or objects, as well as the movement of their bodies or gestures, based on the reflections and deflections of the signals. Wi-Fi employs radio waves, also known as radio frequencies (RF), as a means of communication or connection between devices. RF is measured in gigahertz (GHz), with 2.4 GHz (IEEE 802.11b/g) or 5 GHz (IEEE 802.11a) being the frequency range bands or channel sizes for signals [24–26, 30]. People connect their personal computers (PCs), laptops, mobile phones, and other devices at home using Wi-Fi 802.11 networking technologies, and some urban communities are utilizing this technology to offer their residents low-cost or free internet access. However, wireless networking may become so prevalent that everyone can access the internet anywhere and anytime without using wires. The rationale behind the Wi-Fi channels is to diminish interference, obstruction, and overlap between other Wi-Fi devices or gadgets and the users' Wi-Fi devices.

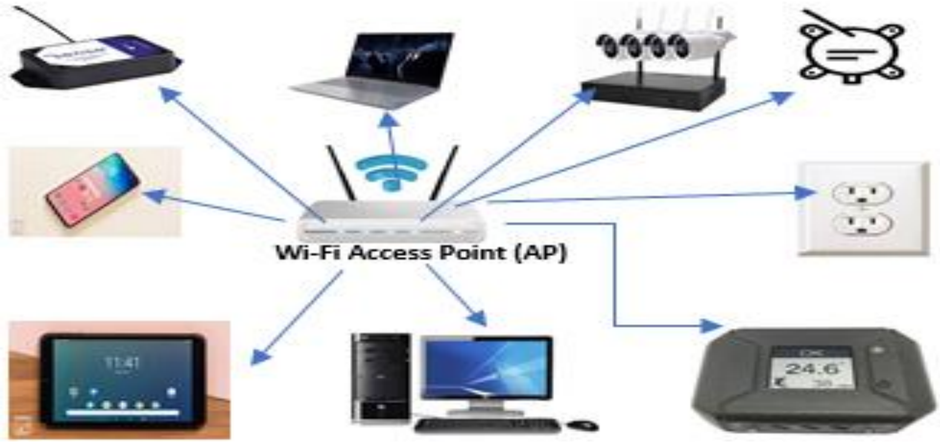

Fig. 2. A passive Wi-Fi sensing system

According to Tom Li (2020), Wi-Fi sensing is a kind of short-range radar technology (passive system) that is amazingly accurate. It can effortlessly detect a human gesture or any object movement for activity classification in any type of environment, be it indoors or outdoors. A strategically placed sensor or group of sensors can monitor activities during large events in complex environments. For instance, elderly care services and hospitals can use Wi-Fi sensors to detect simple human movements like sitting, talking, standing, walking, running, falling, pushing, kicking and so on. These sensors are also able to detect other movements, such as limb movements, heartbeats, pulse rates and breathing, through biometric data [31, 81–83].

Furthermore, Wi-Fi sensing does not require additional hardware, unlike active radar systems that require dedicated transceivers and antennas, which can be considerably costly and complex. This makes Wi-Fi systems highly advantageous over existing systems. For most applications, users only need to install the necessary software to transform and use existing devices such as PCs, cell phones, laptops, and mesh Wi-Fi systems [30, 31].

3.0 DEVICE-FREE HAR METHODS USING WI-FI SENSING ENVIRONMENT

The Wi-Fi signal was among the first to be utilized for HAR purposes because of its universal presence with deployed infrastructures [33], as Wi-Fi signals can penetrate human bodies and other objects, including furniture, walls, doors, and so on [34, 35, 36], as shown in a typical Wi-Fi sensing signal reflection in Fig. 3, and Table II provides a comprehensive summary of device-free HAR in a Wi-Fi sensing environment.

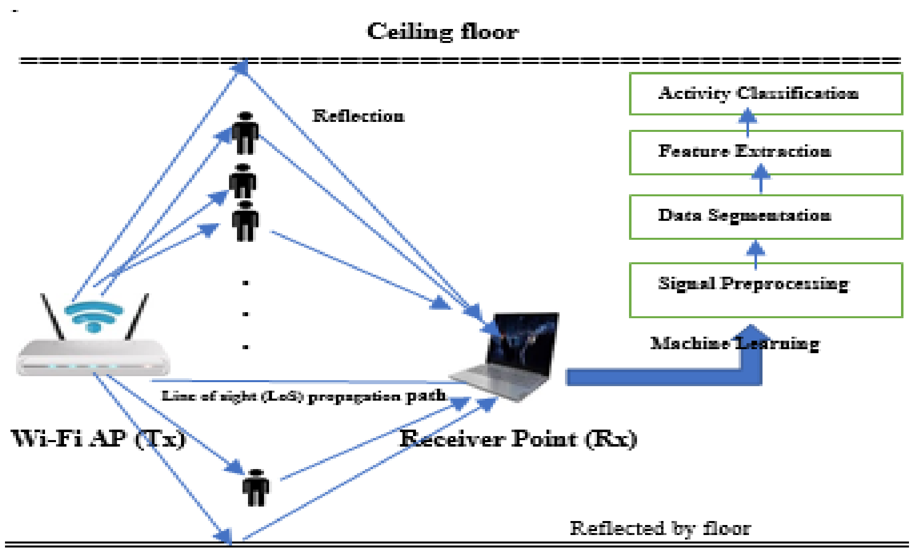

Fig. 3. A typical device-free Wi-Fi sensing signals reflection in a smart home environment (based on human activity)

Table 2: Provides a Comprehensive Summary of Device-Free HAR in Wi-Fi Sensing

Reference	Problem addressed	Methodology / Models	Dataset(s) / Environments	Human activities	Performance	Limitations/ Challenges
Wenjun Jiang et al. [41]	When applied to another person's activities recorded in a different environment, the HAR model does not perform well in terms of prediction	EI device activity recognition framework, a deep-learning based, Convolutional Neural Network (CNN)	Different rooms (40), Wi-Fi, visible light, millimetre wave	Sitting down, standing up, wiping the white board, walking, rotating the chair, and moving a suitcase	10 statistic features (time domain, frequency domain) accuracy of 0.6 without balance constraint, 0.75 with balance constraint	Lack of complex activities
Xuangou Wu et al. [42]	Existing HAR systems do not meet the set-ups of the signals over the wall or require dedicated devices	TW-See, opposite robust PCA (Or-PCA), BP Neural network	6 volunteers, 3 types of sampling environments (CSI), 320 samples (activity), 1680 samples (training), 560 samples (validation)	falling, hand swinging, boxing, walking, sitting down, standing up, no activity	94.46% HAR accuracy and good robustness	Hyper parameters and classification model are not ideal for environment 3
Heju Li et al. [43]	Existing Wi-Fi CSI based systems minimally leverage the amplitude and phase information.	WiFi CSI, Discrete wavelet transform, WMA method, SVM	10 users, 5 CSI Samples	Bending, jumping, stepping, half squatting, stretching legs	An accuracy 98.5% from 5 simple activities	Inadequate training samples, very limited (simple) activities, no overlapping activities
Guanhua Wang et.al.[44]	Most of the Wi-Fi signals are unable to detect human motion and locations or hear people talking without deploying any aided devices	commercial Wi-Fi infrastructure and USRP N210 platform, Multi-Cluster Feature Selection (MCFS), dynamic time warping (DTW)	4 users (3 males, 1 female)	Pronouncing some simple vowels and consonants (like, is, the, he, she, you, see, good, how, are, fine, look, open, sing, meet, watch, lady, horse, etc.,)	91% detection accuracy based on the trained data	Inadequate testing on different angles by deploying multiple receivers, mostly simple commands and conversations, training overhead, real-time tracking
Raghav H. Venkatnarayan et al. [45]	In WiFi-based gesture recognition systems, it is not possible to identify the motions of multiple humans performing actions at the same time.	WiFi based Multi-User (WiMU) gesture recognition system,	195300 training samples	6 gestures	95.0 (2), 94.6 (3), 93.6 (4), 92.6 (5), 90.9% (6)	Virtual samples-based scenario
M.A.A. Haseeb, &	Most of the Wi-Fi based gesture	Wi-Fi access points (AP),	Sample Gesture	4 data sets based on 3	Wisture recognition	Data set 3 shows a poor

R. Parasuraman [46]	recognition methods require a modified hardware device or OS to identify the gesture recognition	smartphone (Wi-Fi RSS), LSTM RNN based	windows (Left-Swipe, Right-Pull, Middle-Push)	gestures (pulling, swiping, pushing)	accuracy is 93% (data set 1, 2, 4) (average 78%)	recognition accuracy, limited gestures
Zengshan Tian et al. [47]	Lack of system to recognize the accuracy of motion of hands by using channel state information (CSI)	WiCatch, commercial WiFi, Support Vector Machines (SVM), GDC algorithm,	a typical indoor environment, single user	9 test gestures (pushing, pulling, waving, sliding, rightward, leftward, rightward, boxing, opening the fridge, opening window)	A recognition accuracy of over 96% for single-hand gestures and 95% for two-hand gestures	No other sophisticated human gesture detection such as jumping, walking, running.
Lei Wang et al. [48]	Previous WiFi signal HAR-based systems don't work well for high-precision tracking and don't provide enough accuracy for gesture tracking	CSI, WiTrace, Kalman filter, USRP, Estimating Initial Position Algorithm, 1 transmitter, 2 receivers	Indoor environment, Transmitted frame - 64 subcarriers, data -48 sub carriers, pilot - 4 subcarriers	walking, running, standing	Initial position – 3.91 cm, mean tracking errors - 1.46 cm (1D tracking), 2.09 cm (2D tracking)	Did not originate the accurate CSI phase, proposed algorithm takes prelude gestures recurrently
M.A.A. Al-qaness [49]	Traditional HAR methods adopt special devices to track both macro- and micro-activities	1 TP-link WR845N with two antennas, 1 laptop with IW5300 NIC with three antennas, RSSI, CSI, Confusion matrix, Butterworth filter, PCA	Indoor environment, 10 users, 500 samples, micro activity, 10th cross validation	Localization, motion detection, recognition (daily activities, hand gestures), such as pushing, dodging, striking, pulling, dragging, kicking, punching and bowing	Accuracy - none line of sight (NLOS) 89.147%, line of sight (LOC) 91%	Sensitivity of CSI to human motion due to testing two or more users concurrently
Y. Wang et al. [50]	Traditional HAR approaches involve wearable sensors and specialised hardware installations	Wi-Fi 802.11ac, CSI based human behavior recognition, pattern-based approach, dynamic exponential smoothing filter, earth mover	indoor environment, 4 volunteers, 9 typical in-place, 8 walking activities	8 type of walking movement, 9 in-place activities	96% average rate using 3 devices, 92% detection with only one device.	no multiple persons, other objects only tested with a single occupant, stable environment

		distance technique				
Wei Wang et al. [51]	The absence of a quantitative model that correlates the dynamics of human activities	Wi-Fi, CARM (CSI human Activity Recognition and Monitoring), quantitatively, correlation, dynamics for a specific human activity, PCA, HMM	Lab, apartment environment, 1,400 activities samples from 25 (20 males, 5 females) volunteers.	Empty (no activity), running, sitting down, walking, falling, boxing, pushing one hand, brushing teeth, opening refrigerator	CARM achieves greater than 96.5%	Less scenarios in the training set, no multi person activity
W. Wang, A.X. Liu & M Shahzad [52]	There was an accuracy defect in prior gait-based human recognition schemes using cameras, floor sensors, and wearable sensors.	commercial WiFi, WifiU-Commercial Off-The-Shelf (COTS), Gait based human behavior recognition, Pattern-based approach using LibSVM tool with RBF, PCA	Room environment, 2,800 instances from 50 human (walking) with an area of 50 sq.mtr.	Gait features (limb movements) including cycle time, spectrogram signatures, walking speed, etc.,	WifiU recognition accuracies are 79.28% (top-1), 89.52% (top-2), 93.05% (top-3)	No multi person activity, predefined walking direction, current WifiU implementatio n is only suitable for confined spaces
Yunze Zeng et al. [53]	Lack of a user's identity and activities from a small group of people using WiFi in a device-free manner	Wi-Fi 802.11n, WiWho framework, CSI, Butterworth bandpass filter, Pattern-based approach using decision tree.	Room environment, single user activity, 3 different locations, 20 volunteers	Human identity, Gait patterns (limb movements) 2-3 meters,	2 to 6 human activities, recognition accuracy is 92% - 80%.	Moderate accuracy, single person, walking path is a straight line and there is no identification of the steps and gait when person turns while walking, lack of feasibility, lack of detection if a person is outside the group
Hao Wang et al. 54]	There is insufficient precision to identify human daily activities (fall detection) in a natural and continuous manner, without the need for any devices	Wi-Fi 802.11n/ac CSI based HAR, Real time (RT) fall method, Pattern-based approach (SVM), band-pass filter, 1-D linear interpolation	Single user, room environment, over two months with 6 (5 males, 1 female) volunteers, using LOS, NOS Scenarios	8 fall detection features (sitting, standing, lying down, picking up, squatting, walking, upper body activities, standing up, sitting down, standing-	91% sensitivity, 92% specificity (WiFall with other methods,1 0% higher specificity, 14% higher sensitivity on average)	Unsuitable when several daily activities are performed continuously and naturally

				falling, walking-falling)		
Jin Zhang et al. [55]	The WiFi spectrum presents an unresolved issue of human identity, specifically the unique identification of each individual	WiFi-ID CSI, A silence removal method, Butterworth filter, Pattern-based approach, Sparse Approximation based Classification (SAC)	10 persons - training, 20 persons – testing	Human identify (walking style, body shape),	2 to 6 individual, accuracy rate 93%-77%	a simple scenario not more generalized solution, simple set up such as group size of 6 people
Tong Xin et al. [56]	Existing human identification methods are plagued by sensing coverage ranges and user privacy issues	WiFi CSI, IIR filter, Butterworth, Pattern-based approach (k-nearest neighbor (KNN) classifier, DWT, DTW, PCA	Single user, indoor human identification environment, 40 samples from 9 volunteers	Human identity (walking pattern)	Human identification accuracy (2-6 individuals) is 94.5% - 88.9%	Not practical for smart home usage, Testing based on only one person, not more than one person in the same space
Don Wu et al. [57]	The indoor environment lacks a cost-effective and continuous solution for human walking direction	Wi-Fi CSI, Fresnel zone, spatial and time domain feature, polynomial smoothing filter, direction estimation, cross-correlation denoising	Indoor environment, 3 rooms, 1289 paths (room A -856 paths, room B, C – 433 paths), 5 volunteers	Human tracking (walking direction)	Less than 10 degrees median error (walking direction).	Multi-path Influence (localization, gesture recognition), Detection Range and Device Placement, no multiple persons, Grid approximation
Chen-Yu Hsu et al. [58]	An inadequate model to track users' behaviour sensing at home, which primarily relies on self-reporting,results in significant overhead and is not sustainable in the long term	Spectrogram, FMCW chirp model, CNN, Principal Component Analysis (PCA)	1-month deployment (6 homes),	human tracking (behavioral sensing)	85% - 95% accuracy ranges, 90% average across all homes.	Accuracy not great when multiple users moving especially without filtering mask
Chitra R. Karanam et al. [59]	In RF-based past works on HAR, they identified either a single-person movement or a multiple-person movement by using a large number of receivers or	Wifi CSI, AoA model, ToF, multipath mitigation AoA, 2D MUltiple SIgnal Classification (MUSIC) algorithm	Both indoor and outdoor environment, 1-3 users, 40 experiments of tracking, 3 laptops, 1 transmit antenna	Indoor, outdoor - multiple human walking in an area	Highly accurate tracking – outdoor 38cm (mean error), indoor 55 cm (mean error)	Tracing through walls, Presumptuous knowledge of the number of people

	some additional resources					
Biyun Sheng et al. [60]	Existing HAR models rely on traditional features, and their design is still difficult, with limited information and a negative impact on recognition accuracy.	Wifi CSI, Two-Stream, Convolutional Neural Network (CNN), LSTM, KNN	two scenarios (Lab, Meeting room) 420 samples from 2 indoor environment	Indoor and outdoor, simple 7 human activities (waving, pulling, clapping, boxing, throwing, bending)	Accuracies is 97.6% and 96.9% from 2 indoor environme nt	Static human activities, no overlapping (complex) activities

Depatla et al. (2015) presented a Wi-Fi-based system that uses only RSS measurements between a pair of transmitter and receiver antennas to count the number of people walking in a given region [87]. The two main ways that individuals can impact the Wi-Fi signal's propagation by blocking the LOS signal and by scattering effects are the foundation of the suggested framework. After creating a simple motion model, they used mathematics to explain how a crowd might block the line of sight. Lastly, they provided a mathematical description of how the number of participants affected the scattering and multipath fading that resulted. By combining these two effects, they were able to develop a mathematical equation that represented the population's probability distribution of the received signal amplitude. For instance, the standard Wi-Fi omnidirectional antennas consistently achieved an error of two or less 63% of the time in the indoor situation and 96% of the time in the outdoor case. Employing directional antennas consistently achieved an error of two or less in both outdoor and indoor settings [86].

Xu et al. (2013) proposed that up to four people's numbers were counted using numerous Wi-Fi nodes and RSS readings. About 84% of the time, they reported accuracy within one person's error. Seifeldin et al. (2013) proposed a similar method that was applied, and they were able to count up to three people with fewer nodes. Nakatsuka et al. (2008) proposed a transmitter-receiver pair to be employed to calculate the population size using RSS readings. The underlying model was developed using a large amount of training data; in experiments with a maximum of nine participants, errors of up to six individuals were observed. Xi et al. (2014) measured the CSI of several sub-carriers and created a model that connected the CSI to the number of people who completed a training level. To test their model, they counted up to nine people using one transmitter and three receivers. Nevertheless, the majority of modern Wi-Fi cards lack the ability to measure the CSI of various sub-bands. Lv et al. (2013) counted up to three stationary people behind walls using UWB radar. In He et al. (2014), the authors employed machine learning approaches to estimate the population using a pulsed radar. A people-counting method based on CSI measurements was proposed [91]. The suggested method's fundamental tenet is that an accurate population estimate can be obtained by examining the CSI's changes. The relationship between the number of moving people and the variation of the wireless channel was investigated theoretically and empirically verified. Their findings demonstrate that CSI is very susceptible to environmental influences and that there is a monotonic relationship between CSI changes and the number of people travelling. This offers a reliable foundation for crowd counting.

The proposed statistic is the percentage of non-zero components in the CSI matrix. The metric can quickly measure changes in CSI and determine the number of people. The metric's value rises with the number of active individuals, reaching saturation when that number of individuals crosses a particular barrier. The number of people was estimated using the Grey-Verhulst model. A grid array composed of several devices was used to estimate the population of a sizable area. The primary obstacle was that CSI is highly environment-sensitive; that is, user movements inside one grid will cause CSI fluctuations in neighbouring grids. An interference cancellation technique was developed to modify each receiver's sensing range in order to improve estimation accuracy across a widely monitored area. 802.11n Wi-Fi devices were used in the system's construction. Large-scale trials were used to assess the system. The outcomes demonstrated that, in terms of accuracy and scalability, the suggested approach performs better than alternative approaches [86–87].

The locating process was split into two phases, namely the operating stage and the training stage. The localization problem was reformulated as a probabilistic classification problem in order to address the inaccuracy resulting from multipathing in packed environments [94–95]. Yuan et al. (2011) estimated the number of people using a categorization system. Arai et al. (2010) suggested a method to connect the radar chart feature and the patterns of crowd movement. For this method, building a fingerprint database requires surveying the locations that are used. The primary drawbacks of this strategy are the work, expense, rigidity, and environmental dynamics. The cost of training is a major barrier to crowd counting, especially in large-scale situations. Obtaining the ground truth is also extremely difficult in situations where there are a lot of participants.

In [97, 98], the RSS will change significantly if the user is close to a link. Moving away from the link, however, causes the performance to drop off quickly. Nakatsuka et al. (2008) demonstrated the usefulness of estimating crowd density using RSS average and variance. A statistical method to estimate the RSS variance as a function of an individual's position with respect to the antenna locations was proposed by Patwari et al. (2019). Using RSS data, Xu et al. (2013) estimated the number of people and pinpointed their locations using a link-based method.

The Wi-Fi sensing signal contains a Wi-Fi access point (Tx-Transmitter or transmit wireless signal, an Rx-Receiver Point or receive wireless signal), and/or one or a few Wi-Fi aided devices in the smart environment where a typical device-free human activity or group of people movement occurs. This environment can include the ceiling, floor, and other objects and can be either indoor or outdoor. Whether the environment is indoors or outdoors, we can recognize human activities. Every movement of a human body in a smart home influences wireless signals due to the presence of water in the body. This continuous reflection (multi-path) in Wi-Fi signals occurs whenever a human moves within the line of sight (LOS), causing changes in signal reception. Therefore, the Rx Wi-Fi device detects a diverse received signal strength (RSS) [23], [34–36]. The Wi-Fi signal will spread in a multi-path manner, and the wireless channel will be comparatively stable as long as no human body movement occurs [23], [38], [40] [79].

The existing Wi-Fi AP (Tx) transmits a series of ideal packets, which the Receiver Point (Rx), which could be either a laptop or PC, receives for collection and processing. Hence, we are able to detect human activities based on this principle by exploring the changes in wireless signals caused by human movements [39], as shown in Fig. 3. Applying appropriate classification methods or HAR algorithms accurately identifies the type of human behavior, thereby enabling presentation layer application. Notably, most of the recent and current research on smart home models shows that CSI and RSS indicators are the two main ways to recognise human activities in a Wi-Fi environment. Compared with RSSI, the newly developed CSI is a more fine-grained methodology that defines both phase shift and amplitude attenuation of the wireless signal. Its application is able to recognize various human behaviors effectively, from simple activities to complex actions. The receiver (Rx), typically a personal computer or laptop, measures the collected CSI data from the Wi-Fi access point device (Tx). The Wi-Fi AP generally comprises some antennas that form multiple data streams from the transmitter (Tx) to the receiver point (Rx). We can adjust the frequency of data packets from the Wi-Fi access point device to suit our experimental needs. Next, apply the data pre-processing task to collect accurate CSI data for further aggregation. After gathering CSI data, data pre-processing is required to get more precise data by employing diverse types of filters to eliminate the noise from the collected data.

Subsequently, diminishing device interference and ambient noise requires effective de-noising models in order to separate a multivariate signal into additive subcomponents [37] by using one or more computational methods such as conventional Independent Component Analysis (ICA), Locally Linear Embedding (LLE), Linear Discriminant Analysis (LDA), Principal Component Analysis (PCA), t-distributed Stochastic Neighbor Embedding (t-SNE), and other machine learning algorithms (for example, autoencoders). Since the job is dependent on detecting unusual human behaviors, it is necessary to prioritize feature extraction that specifically focuses on 'extracting anomalous motions from activity' in order to improve prediction accuracy. Nevertheless, LDA and PCA are the prevailing techniques employed in intelligent IoT setups for the purpose of extracting features. After successfully preprocessing the data, we typically separate the consistent CSI data streams into segments based on amplitude or frequency dissimilarity. Typically, each portion would contain an entire action or a breath cycle. Therefore, we can use these segmentations to illustrate the duration of activities by calculating their velocity [37]. Finally, we need to apply the classification method to recognize human activities. The behavior of gratitude is typically a classification problem and can be implemented using edge setting or any common machine learning algorithm that is more appropriate based on the requirements.

In this context, people use smart devices to assess human wellness [61]. Even so, the arrangement becomes cost-effective because it frequently necessitates replacing the existing equipment. Because they are simple to install, environmental Internet of Things (IoT) sensors are regarded as one of the most popular nonintrusive sensor types, along with pyroelectric infrared (PIR) motion sensors [62–64, 81]. These are also suitable in terms of cost-effectiveness and low power usage. However, because of their inherent flaws, such as low battery life and high maintenance requirements, the aforementioned technologies might not be useful for long-term activity detection applications. Consequently, the unobtrusive system—which is non-privacy-invasive and device-free—is the best option for long-term, real-world activity recognition. Machine learning (ML) and Probabilistic are two methods that are now in use for behavioral detection at home and can be defined [18]. While some strategies work on context-aware bases measured from raw data, few apply directly to sensor data. Only a few strategies, nevertheless, appear promising for real-time activity monitoring, and most methods for raising false alerts are criticized by detractors.

4.0 LIMITATIONS, AND CHALLENGES IN DEVICE-FREE WI-FI SENSING ENVIRONMENT

In the preceding sections (I, II, and III), we have specified the Wi-Fi sensing capabilities of HAR based on the analysis of past research, which shows outstanding potential in a smart home automation environment. Nevertheless, the vast majority of these results and conclusions are inadequate in terms of scientific research. Therefore, we need to address some of the challenges to cover the practical aspects effectively. The following is a list of these challenges and limitations for Wi-Fi HAR sensing research.

4.1 Effect of Environmental Interference

Wi-Fi signals are vulnerable to environmental interference that diminishes their accuracy rate. If the sensors encounter heavy traffic, it may have an impact on the quality of service. Indoor environments are more challenging than outdoor environments because Wi-Fi signals in indoor environments spreading through multiple paths will experience more variations, such as ceilings, roofs, floors, and other objects that are placed in the environment. Additionally, dissimilar human bodies can cause diverse fluctuations at the receiver end. Furthermore, the impact of higher false alarms, noisier spectrums, and stronger multipaths increases the human tracking error. This could affect the HAR model's performance. Similarly, the performance of each new Wi-Fi sensing system may fluctuate. Therefore, human bodies and environmental changes must be carefully considered to build a strong Wi-Fi sensing system.

4.2 Object Interference

The test environment will detect objects or human movements based on variations in wireless signal fluctuations (amplitude and phase information). Any arbitrary gesture by intrusive objects in the test area will cause fluctuations in the Wi-Fi sensing system (received signals). As a result, it will become difficult to recognize the users' movements and their activities.

4.3 Multiple User Activity Sensing

In several applications, including crowd management and guided tours, crowd counting is becoming more and more crucial [87]. However, crowd estimation and counting face numerous difficulties due to the unpredictability of crowd behaviour. Object occlusions and the need for real-time processing present additional difficulties. People counting is useful in a variety of applications. One example is smart building management, which allows heating to be adjusted according to occupancy levels and can save a significant amount of energy. Numerous other such programs exist that can also be enhanced according to the number of users. When a crowd needs to be evacuated from a location due to an emergency, crowd estimation may also be crucial [86]. Currently, both RSSI and CSI have demonstrated excellent performance in detecting a single human activity (HAR) in device-free WiFi-based sensing technologies. However, these technologies fall short when detecting multiple human activities. However, CSI outperforms RSSI in this regard. Despite the current development of CSI-based sensing technology, the simultaneous detection of multiple human activities or objects is still a critical issue. Although MultiTrack [65] is a device-free sensing system that can identify multiple human activities in order to build a signal profile, it requires every individual to complete their activities independently. Therefore, addressing multiple user activities remains a significant challenge in HAR within a Wi-Fi device-free environment.

4.4 Complex Deep Learning and Hybrid Methods

In recent years, deep learning technology has rapidly emerged and has attracted many applications. In the field of wireless technologies, the problem of human position or localization detection has always been a widely debated topic. Moreover, in the current Wi-Fi sensing system, various methods have been used for different constraints; for instance, placing some sensors on the user's body may resolve some limitations in HAR detection. Therefore, to overcome certain limitations, it is necessary to consider hybrid technologies, which involve combining other methods such as deep learning, smart phones, sensors, wearable devices, and so on, with device-free Wi-Fi-based methods.

4.5 Lack of Standard Datasets

There have been notable efforts to collect datasets from the device-free Wi-Fi sensing system (both indoor and outdoor environments) to track HAR. These datasets are critical for researchers to establish accurate detection of human activities because accumulating real-house annotated datasets is tedious, time-consuming, costly, and difficult to find. A few standard datasets are publicly available. Smart home datasets like CASAS [66], OPPURTUNITY [67], ARAS [68], Kasteren [69], House-n [70], HIS [71], and Ordonez [72] help to find people who are moving around because they provide a starting point for testing different machine learning methods. However, these datasets are not sufficient for all environments, as each new environment requires the system classifier to be trained with new data due to the diverse testing results of the smart home and the high cost associated with processing bulky training datasets.

5.0 DISCUSSION AND FUTURE DIRECTION IN DEVICE-FREE WI-FI SENSING

In previous sections of this article, some key challenges and limitations were identified, which include multipath propagation, obstruction of the Wi-Fi signal, multiple user recognition, accuracy of human behaviors, object interference, hybrid method deployments, and so on. However, these systems do not yet address some real-world challenges that enable application in real-time device-free Wi-Fi sensing systems and their environments. Aside from that, many of the existing systems only function well in controlled environments. Moreover, the precision of these systems is affected by many aspects, such as human gestures in neighboring areas, multi user gestures, limitation range resolution, orientation of transceivers, changes in distance from Tx to Rx, and so on.

The deep learning sensing application frameworks represent an intriguing research area that has drawn the attention of many researchers, despite being at a preliminary stage due to their potential for adaptation in real-time environments. Furthermore, these deep learning sensing application frameworks effectively utilize the Convolutional Neural Network (CNN) method to achieve excellent results when eliminating features and group HAR activities [73–78]. However, further research is necessary to enhance the CNN deep learning model by incorporating expert knowledge. With the above key points in mind, we strongly recommend the research community probe further into device-free Wi-Fi sensing human activity as part of their research endeavour to enable the development of innovative methods and improve the current models to enhance their value in real-time applications.

Throughout the analysis, certain obstacles pertaining to Wi-Fi sensing systems and their uses have been identified. In order for these systems to function in real-world settings, they still need to overcome a few obstacles. One such obstacle is multipath propagation. The Wi-Fi signal is being blocked due to the large number of individuals present. Additionally, many of the suggested systems are only effective in controlled settings; a variety of variables, such as shifts in the direction and distance of the transceivers and movements made by people in the vicinity, can impact their accuracy. Lastly, compared to other sensing technologies like UWB (Sobron et al. (2018)), Wi-Fi has a lower range resolution, which may restrict the range of applications.

6.0 CONCLUSION

In recent years, context-aware researchers have shown a lot of interest in the HAR on device-free Wi-Fi sensing mechanisms. This paper has presented a comprehensive review of different Wi-Fi device-free sensing systems and their applications. We also emphasized the limitations and key challenges of existing works, and highlighted interesting upcoming research directions. Also mentioned the shortcomings of previous works, along with several intriguing ideas for future research. This sensing system does not require a wearable or special device to monitor human activities, which rely solely on wireless signals. Signal deflection could be used to detect human motion. Though device-free Wi-Fi sensing techniques have already been applied in many sensing applications, including human activity detection and localization. However, we still need to address a number of challenges to efficiently identify human gestures in complex environments. Consequently, by conducting more in-depth research to identify solutions that can address the present challenges, we believe that device-free Wi-Fi sensing techniques will emerge as the future backbone of HAR.

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