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Smart Home Based on WiFi Sensing: A Survey

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ABSTRACT Conventional sensing methodologies for smart home are known to be labor-intensive and complicated for practical deployment. Thus, researchers are resorting to alternative sensing mechanisms. Wi-Fi is one of the key technologies that enable connectivity for smart home services. Apart from its primary use for communication, Wi-Fi signal has now been widely leveraged for various sensing tasks, such as gesture recognition and fall detection, due to its sensitivity to environmental dynamics. Building smart home based on Wi-Fi sensing is cost-effective, non-invasive, and enjoys convenient deployment. In this paper, we survey the recent advances in the smart home systems based on the Wi-Fi sensing, mainly in such areas as health monitoring, gesture recognition, contextual information acquisition, and authentication.

INDEX TERMS IoT, smart home, WiFi sensing.

I. INTRODUCTION

Smart home enables the interconnections of ubiquitous devices planted in home appliance with sensors and actuators for automation [1]. The thrust for smart home is an aggregation of different kinds of technologies which normally involve three layers [1], [2]: application layer, network layer, and perception layer. The perception layer is responsible for gathering information from the surroundings and serves as the interface for humans to interact with the connected objects. The desire for more comfortable and friendly to use interface has led to the development of ubiquitous and novel sensing methodologies.

Conventional sensing methodologies for smart home have several shortcomings. First, it usually involves different kinds of sensors [1]. But different sensors have to be activated by different drives for data acquisition. Thus device drive development for the numerous sensors would be a great burden. Second, the installation of various sensors for smart home is costly. We have to deploy dedicated devices and sensors at geographically dispersed locations [1], [3], [4], which may require special technicians to set up. Finally, popular interaction solutions with everyday objects require explicit user input which is still not convenient. For instance, the popular smart home products such as Amazon Echo [5] and Google Home [6] require audio input. A smart home system that can non-invasively anticipate our needs and act in advance without much intervention would be much more desirable. Therefore, researchers have been searching for new possible solutions.

Recent advances in wireless technology have found that the WiFi signals are sensitive enough to capture environmental dynamics thus can be used for the sensing purpose. Building a smart home based on WiFi sensing can outweigh conventional solutions. The main benefits are threefold. 1) Cost-effective. WiFi sensing makes it possible to deploy sensing tasks on existing infrastructures, namely WiFi transceivers which are already ubiquitous in typical indoor settings. 2) Convenient deployment. Building supported hardware for smart home is simple and easy. We just need to place a pair or several pairs of WiFi transceivers in the place of interest. Literary works [7], [8] even claim that random placement is also feasible. And the software to expose sensor readings has been released in the community [9], [10]. No extra efforts for device drive development are needed. Therefore, we can have a convenient deployment. 3) Non-invasive sensing. WiFi sensing, either active or passive, uses the invisible radios to sense the surroundings, thus eliminates the reliance on the direct contact. It can accomplish the sensing tasks without user awareness thus introduces no discomfort. Such non-invasive sensing also enables continuously over-the-air monitoring, making it feasible for the radios to "recognize" the users and "understand" their behaviors.

WiFi sensing has been used in many fields. For instance, Virmani and Shahzad [7], Wang *et al.* [8], and Wang *et al.* [11] proposed to use WiFi signal to identify human activities, providing us opportunities to design new human computer interfaces for smart home automation. Works that proposed to leverage WiFi signal for respiration monitoring and heartbeat detection were presented in [12], [13], and [14]. Such works make non-invasive healthcare monitoring available. Utilizing the WiFi signal to extract contextual information such as location, direction, or range information had been demonstrated in [15]–[17]. Combined with Augmented Reality (AR) or Virtual Reality (VR), these works may offer us a brand new experience for smart home entertainment. These insightful works open up doors to enhance functionalities for smart home on existing infrastructures with little efforts.

In this paper, we survey state-of-the-art processing algorithms, applications, and systems based on WiFi sensing. We present these works into the following four categories: health monitoring, gesture recognition, contextual information acquisition, and authentication. We have summarized the literary works corresponding to each category in Table 1. In later sections, we will divide into the principles behind each category. In the end, we also highlight the challenges and envision future research trends.

TABLE 1. Summary of WiFi-based applications.

Category	Applications
Health monitoring	Hearbeat detection [14], [18] Respiration rate monitoring [12], [13] Sleep apnea detection [12] Fall detection [19], [20]
Gesture recognition	Human activity recognition [7], [8], [11], [21] Keystroke detection [22] Sign language recognition [23] Lips motion recognition [24]
Contextual information acquisition	Location [16], [25]–[27] Direction finding [15], [28]–[30] Range estimation [17]
Authentication	Access control [31] Intrusion detection [32], [33] Abnormality detection [32], [33]

II. A PRIMER ON WiFi SIGNAL

WiFi sensing is an emerging concept that uses WiFi radios as sensors [34]. In this section, we present preliminary knowledge on WiFi signal. Specifically, we introduce two numerical "sensor" readings, namely Received Signal Strength Indicator (RSSI) and Channel State Information (CSI).

Received Signal Strength Indicator (RSSI) defines the relative power strength of the received signal. In IEEE 802.11 standard, RSSI is internally used to reflect a link quality [35]. RSSI follows the Log-normal Distance Path Loss (LDPL) model [36]:

$$P(d) = P(d_0) + 10nlg(\frac{d}{d_0}) + X_\delta, \quad (1)$$

where $P(d)$ is the power strength at distance d, $P(d_0)$ denotes the power strength at a reference location d_0, n is the power loss coefficient, and X_δ is a random noise. Based on Eq. 1, we can roughly get the relationship between distance and the power strength. However, in a complex indoor environment, the multipath effect [36] will greatly distort the model, making it almost impossible to infer location from Eq. 1. Fig. 1 depicts the RSSI measurements corresponding to different WiFi APs in a fix location. We can see that RSSI can fluctuant heavily, making it an unreliable indicator.

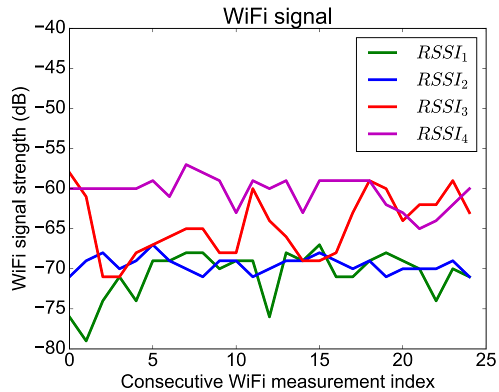

FIGURE 1. RSSI measurements corresponding to different WiFi Access Point in a fix location.

Channel State Information (CSI) is a much finer grain metric than RSSI. CSI has been widely adopted in wireless communication especially in modern Orthogonal Frequency Division Multiplexing (OFDM) systems. The primary function of CSI is to estimate the properties of propagation channel characterized by the environment dynamics, thus adopting better strategies to improve throughput performance [37]–[39]. Assume we transmit a known matrix X, after experiencing some propagation delay, reflection, or other distortions, we get another matrix Y at the receiver end. If we use H denote the CSI, then $Y = H * X$. The CSI in OFDM systems can be parameterized by a vector $\vec{H}$,

$$\vec{H} = (H(f_1), H(f_2), \ldots, H(f_N)), \quad (2)$$

where $H(f_i)$ denotes the Channel Frequency Response (CFR) on each subcarrier. The vector $\vec{H}$ in its complex form characterizes the propagation channels on each transceiver pair, equalizing the channel distortions and contributing to improve the communication performance. The CSI has finer granularity and flexible sampling rate than its well-known counterpart, RSSI, which is a summation of CSI across all the subcarriers and only reflect amplitude information.

The CSI data contains amplitude and phase information. The summation of CSI amplitudes across each subcarrier becomes RSSI [36]. So CSI amplitude obtains the same properties with RSSI. Due to its inherent short wavelength, the CSI phase is much more sensitive to environment dynamics. Say the CSI signal experience $d = \frac{\lambda}{2} = 6.25$ cm displacement (the oscillating frequency of the WiFi signal is 2.4 GHz). Such a displacement would not make the CSI amplitude suffer from great distortion. However, it would cause the phase a 180° significant change. The above intuition serves as the basis for many CSI-based applications.

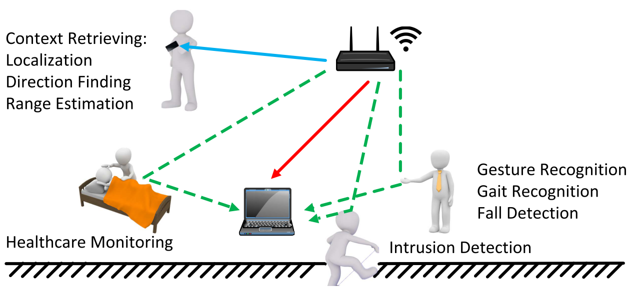

FIGURE 2. An overview of applications based on WiFi sensing.

III. APPLICATIONS BASED ON WiFi SENSING

In this section, we will present state-of-the-art applications driven by WiFi sensing, which can be divided into four categories: health monitoring, gesture recognition, contextual information acquisition, and authentication, as shown in Fig. 2.

The physical layer configurations for these applications normally involve one pair or several pairs of WiFi-enabled transceivers to be deployed in different places. The processing layer for these applications can be generalized into model-based or learning method based. Some works may combine the two models together.

Model-based methods build the systems in a divide-and-conquer manner, consisting of a pipeline of signal processing blocks. Some works [19], [20] may simply regard WiFi as a one-dimensional signal, and naively extract features from the mean, average, deviation, abrupt changes, or even the spectra for use. Others [40] may adopt more advance signal interference models, such as Fresnel zone model, to parameterize the signal properties and trace the model parameters for event detection. Some other works [28], [30] exploit more information from the WiFi architectures, for example, Multiple Input Multiple Output (MIMO) and multiple subcarriers to enhance the reliability.

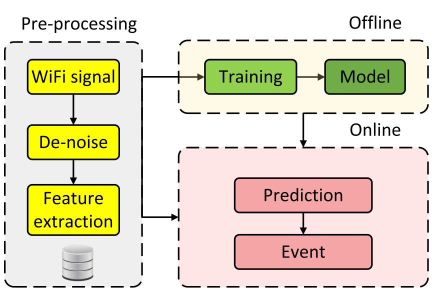

FIGURE 3. Typical workflow of learning-based method.

Instead of explicitly finding a perfect model, some researchers resort to machine learning techniques. The typical workflow has been depicted in Fig. 3. Machine learning based methods typically involve two steps: the offline training and the online predicting. The offline training step is supposed to produce a model, which correlates certain events to the specific features of WiFi signal. When the system is online, the WiFi signal, after some pre-processing procedures, namely de-noising and feature extraction, will be fed into the model to predict certain events.

A. HEALTH MONITORING WITH WiFi SENSING

Health monitoring systems with anomaly detection techniques can trigger an alarm in emergencies, which is quite useful to help take care of patients, babies, and elders.

Currently, most of the health monitoring systems depend on dedicated devices. Many are limited to clinic use and require a well-trained technician to set up [41]. Even though there are some portable devices developed for household use, they are still far from user-friendly and require specialists to instrument the sensors [42], [43]. To make matters worse, some medical disorders, such as sleep apnea, when breathing becomes abnormal during sleep, need constant monitoring. In the clinic, doctors often use polysomnography test to diagnose sleep apnea, which is expensive and laborious [41]. So a non-invasive method is more desirable.

Fall detection is a typical health monitoring system. Falls are the major cause of fatal injuries and death to the elders [44]. It is reported [44] that in the United States, an older adult falls every second of every day, making falls the number one killer of the older Americans. Fall detection has already been discussed in the community. Literary works [45], [46] apply wearable technology to detect fall. Others [3], [4] deploy dedicated sensors in the home. Computer vision [47], [48] based methods are also available. Wearable technology requires users constantly wear a special device, which may cause discomfort. Planting dedicated sensors in the home requires special technicians to do the setup, which is costly and labor-intensive. Computer vision technology seems to be perfect, however, raises privacy issues and can not work in Non-Line-Of-Sight (NLOS) scenarios.

Health monitoring systems with WiFi sensing are promising alternatives to overcome the above limitations. By leveraging the invisible WiFi radios, the sensing tasks can be completed without user awareness, which causes minimum discomfort. The WiFi radios can traverse through walls, making it feasible to perform sensing tasks even under challenging NLOS scenarios. The multipath effect, which is normally detrimental for data communication, can have a beneficial effect on WiFi sensing as it extends the spatial sensing dimensions. We now introduce WiFi-enabled systems capable of detecting biomedical information, for example, respiration rate, heartbeat, and abnormal behaviors.

WiFi-enabled fall detection systems [19], [20] harness the fact that a sudden fall can cause abrupt changes in CSI values. Wang *et al.* [20] applied the magnitude of CSI for fall detection, reporting 87% detection accuracy. The phase difference across multiple antennas is incorporated to detect fall [19], which proves to be more reliable and robust and achieves over 90% accuracy. Both [19], [20] adopt the learning-based techniques.

To detect the respiration rate or heartbeat is much more difficult, as such activities do not introduce noticeable difference on the numerical sensing results. Hence, such systems often require the transceivers placed near the human body. The rational for respiration rate detection is that the miniature chest displacement can modulate the radio signal, as depicted in Figure 4. When the person inhales, the air the person breathes in will inflate the chest, making the radio signal traverse a much shorter distance. When the person exhales, the radio signal will undergo a much longer distance and experience a relatively stronger path loss. Therefore, the breathing cycle is captured by the WiFi signal. Heart beat can be also detected in the same way.

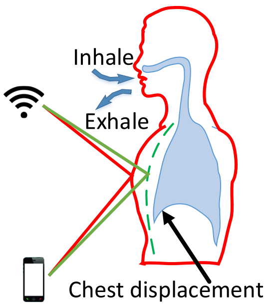

FIGURE 4. The chest displacement can modulate the reflected WiFi signal. So by checking the periodic features of the WiFi signal, we can determine the respiration rate.

Abdelnasser *et al.* [12] and Kaltiokallio *et al.* [13] proposed to use the periodic variances of the signal strength for respiration detection, reporting less than 1 and 0.12 breaths per minute error, respectively. A system that is capable to perform sleep apnea detection based on the estimated respiration rate was presented in [12]. This approach also utilizes the signal strength for estimation, reporting an accuracy of 96%. Liu *et al.* [14] demonstrated that CSI amplitude can be used for vital sign detection. This work can simultaneously estimate heart rate and breathing cycle. The reported mean estimation error for heart beat and respiration rate are within 1 bpm and 0.5 bpm, respectively. The system can work under a single transceiver pair with distances up to 10 m.

The signal strength or amplitude is not so sensitive than the phase information as we have already stated in the previous section. So some scholars resort to phase-based detection method. The researchers from [40] introduced the Fresnel model, the principal of which is the Phase Cancellation effect [49], to estimate the respiration rate. The Fresnel model exploits the fact that the presence of an obstacle in different Fresnel zones, causing multipath effect, can enhance or attenuate the signal strength on the receiver side. Fig. 5 depicts the geometric model of the Fresnel zone for breathing signal extraction. The positions of the transceiver pair are regarded as two focal points of all the ellipses. If the signal propagates and reflected by the boundary of these ellipses, the travel

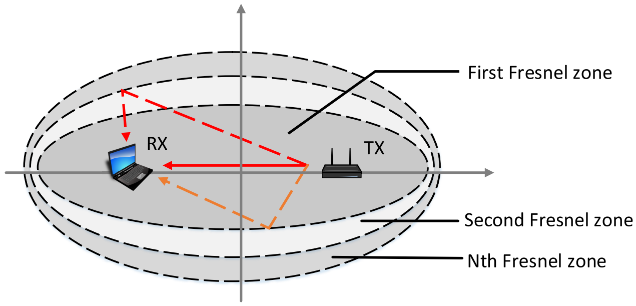

FIGURE 5. Geometric model of the Fresnel zone for breathing signal extraction.

distance subtracted by the LOS signal will be an integer multiple of half wavelength. The inner areas of these ellipses are called the Fresnel zone as depicted in Figure 5. If we place an object in one Fresnel zone, enhancing the signal strength, then in the adjacent zones, it will weaken the signal strength. Thus Wang *et al.* [40] utilized this Fresnel model to convert the chest displacement to phase change for a more robust respiration estimation. It is reported [40] that the system is robust to normal activities and can even detect two different breathing patterns.

B. WiFi-ENABLED GESTURE RECOGNITION

Gestures refer to expressive and meaningful body motions including physical movements of different body parts such as fingers, hands, arms, heads, and faces, aiming to interact with the surroundings [52]. Gesture recognition systems aim to recognize conveyed messages behind performed gestures. Applications of gesture recognition range from recognizing sign language through home automation to virtual reality [52]. It is the key enabler for designing a highly efficient and intelligent Human Computer Interface (HCI). Two well-known commercial gesture recognition systems are Xbox Kinect [53] which is based on vision technology and Wii [54], a wearable device based on the Inertial Measurement Unit (IMU). Vision technology requires the camera directly "see" the gesture performers with a good light condition. And some people may be unwilling to wear specific devices. Wifi-enabled gesture recognition can largely overcome the above limitations since it can achieve device-free. A comparison of related works are depicted in Table 2.

Most of the WiFi-based gesture recognition applications adopt machine learning techniques for pattern recognition. The intuition behind gesture recognition systems is twofold: WiFi signal is sensitive to capture environment dynamics even lip motions [24], and different gestures can produce distinctive signal patterns. If enough data about different gestures and the corresponding signals are collected, a predictive model can be easily trained.

CARM [8] employs only a pair of transceivers for human activity recognition. This approach assumes that the CSI signals across different subcarriers are correlated and employs Principal Component Analysis (PCA) for feature extraction.

TABLE 2. Comparison of the gesture recognition system based on WiFi signal.

Reference work	WiFi signal	Recognizable Gestures	Average accuracy	Number of transceivers
CARM [8]	CSI	Daily activities	96%	1
E-eyes [11]	CSI	In-place activities	92%	1
WiAG [7]	CSI	Activity Recognition	91.4%	1
WiHear [24]	CSI	Lip motion	91%	1
WiFinger [23]	CSI	Hand gestures	90%	1
WiKey [22]	CSI	Keystrokes	77.43%	1
WiGest [50]	RSSI	Hand gestures	96%	1
WiDance [21]	CSI	Motion direction	92%	2
WiDraw [51]	CSI	Hand writing	91%	20

After that, a routine of learning based method is applied: prefiltering, offline training, and online prediction. The activities considered involve running, walking, sitting down, opening a refrigerator, falling, boxing, pushing one hand, and brushing teeth. CARM reports an average accuracy of greater than 96% and is resilient to different environment settings. Similar works include E-eyes [11] that recognizes nine inplace activities, WiHear [24] that recognizes several preset spoken words, WiFinger [23] that understands the American sign language, WiKey [22] that non-invasively tracks the keystrokes, and WiDance [21] that infers motion direction from the WiFi signal.

WiGest [50] is RSSI-based gesture recognition system, which requires at least one pair of transceivers. Since RSSI is less sensitive and less responsive and CSI, the gestures are required to perform near the receiver. The authors first introduce the concept of primitive gesture sketches including moving the hand from different directions and moving with different speed. Then they employ the primitive gestures as preambles to encode messages. For instance, moving the hand up can be decoded as "volume up," and moving the hands up and down can be encoded as "play next track." WiGest reports over 96% accuracy in LOS case and is feasible even in through-wall scenarios.

WiAG [7] borrows the concept of transfer learning to reduce the efforts on training. Conventionally, to improve the recognition accuracy for a specific gesture, many samples need to be collected with different orientations at different locations, which requires heavy workload. WiAG decomposes the gestures into linear and non-linear models and then transfers these models as features. WiAG reports an average accuracy of 91.4% for gesture recognition and an average absolute error of less than 23° for estimating user orientation.

WiDraw [51] represents another line of works that enables gesture tracking based on close-formed solutions. WiDraw requires densely deployed transceivers. It uses the Angle-of-Arrival (AoA) information for hand trajectory tracking. The intuition is that hand occlusion will greatly distort the AoA spectra for a specific link. And if we have a dense deployment of multiple transceivers with known coordinators, the hand traces can be inferred by checking which links are affected. WiDraw enables over-the-air hand writing and reports an average word recognition accuracy of 91%.

C. CONTEXTUAL INFORMATION ACQUISITION WITH WiFi SENSING

Contextual information is the basis for context-awareness applications. Contextual information such as location can enable our computer system to anticipate our needs and act in advance, freeing ourselves from the manually complex configurations and boring instructions. More specifically, the location information can enable a myriad of Location Based Services (LBS). For example, when you enter the sitting room, the light is automatically turned on. After you sit on the couch, the TV is turned on and the luminance of the light dimmers. Such applications would bring great convenience for our daily lives. The contextual information, including location and orientation, open up doors for emerging Virtual Reality or Augmented Reality (VR/AR), providing possible alternatives for us to interact with the world. To retrieve contextual information, three useful signatures can be utilized: WiFi fingerprints, AoA, and Time-of-Flight (ToF).

Fingerprint-based strategies utilize the fact that the features extracted from WiFi signal are context dependent. To be more specific, the waveform or the numerical readings are location and orientation dependent. The fingerprinting strategies typically involve two phases: the off-line phase and the on-line phase. In the off-line phase, a war-drive survey is conducted to collect WiFi signal from different locations in the place of interest. Then the measurements will be labeled by the corresponding locations. During the on-line phase, a matching metric will be applied to rank the off-line labeled measurements according to their distances to the online collected ones in an ascending order. The average of the top k labeled locations will be the estimated result. The fingerprinting approaches usually need multiple WiFi Access Points (APs) in the place of interest. The WiFi signal here can be either CSI [16], [26] or RSSI [25], [27]. The online matching method can be either probabilistic [27] or deterministic [25]. The fingerprint-based method eliminates the reliance on the complex models, which however involves cumbersome survey and is sensitive to environmental changes. The localization result is also not satisfactory, which can be up to 10 m [55].

Fig. 6 depicts a typical architecture for AoA and ToF-based method. It usually involves three pairs of transceivers (for 2D localization, 3D localization is feasible if more transceiver pairs are available).

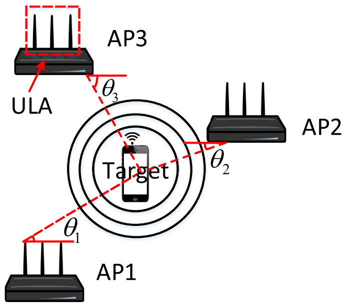

FIGURE 6. Architecture for AoA and ToF-based localization method.

The AoA-based method normally requires either receiver or transmitter to be equipped with Uniform Linear Array (ULA) or Uniform Circular Array (UCA) [56]. With some sophisticated eigenvalue decomposition method such as Multiple Signal Classification (MUSIC) [28]–[30], Estimation of Signal Parameters via Rotational Invariance Technique (ESPRIT), or other signal inference models such as Synthetic Aperture Radar (SAR) [15], the AoA information can be accurately obtained. If three AoAs are available, the location of the target can be pinned down.

ArrayTrack [30] applies MUSIC on ULA with eight antennas to obtain AoAs and uses multiple AoAs to locate the targets. The system achieves 23 centimeter median localization accuracy on an advanced hardware platform. This system may not be directly applicable on most commodity WiFi devices that normally have only up to four antennas, as the MUSIC algorithm works only when the number of antennas is larger than the number of significant reflections.

SpotFi [28] pushes the frontier and makes it possible to deploy MUSIC on commercial-off-the-shelf (COTS) devices with only three antennas. It finds that ToF profiles across different subcarriers on OFDM architecture can be exploited as virtual antennas. Specifically, the Intel 5300 WiFi NIC reports 30 subcarriers information on each antenna and AR93XX/AR95XX serials report 56 subcarriers information. Thus, the number of sensors is larger than the number of significant reflections, making it feasible to apply MUSIC on commodity WiFi devices. SpotFi achieves decimeter-level localization accuracy.

MaTrack [29] is an AoA-based device-free localization system which is built on SpotFi. MaTrack leverages the fact that the presence of an object will introduce another significant reflection, resulting in another peak in the AoA spectrum. And if the object moves, the corresponding AoA shifts simultaneously while the AoAs produced by other static objects or the direct path do not. The object then can be located when multiple AoA spectra are available. Matrack achieves a median localization accuracy below 0.6 m. Ubicarse [15] is another AoA-based localization system. It is device-based and requires the mobile device to rotate and emulate a UCA. Synthetic Aperture Radar (SAR) is applied to estimate the angle of arrival. Ubicarse reports centimeter-level localization accuracy and can even work under NLOS scenarios. Chronos [17] directly measures the ToFs between the transceivers based on multi-tone ranging [57] that utilizes the phase divergence among different subcarriers. Chronos enables single-AP based localization and achieves 4.17 cm ranging accuracy.

D. WiFi-DRIVEN SENSORLESS AUTHENTICATION

User authentication is a vital issue across different industries due to the ever-increasing privacy concern. Systems that leverage biometric signatures [58] or user-owned RFID tag [59] are well-known technologies. Biometric signatures such as fingerprints, face, voices are well-exploited for authentication on smart devices. RFID-based systems are common for companies or government departments to deploy access control. Password-based mechanism which requires user to input the correct characters may be the most commonly used one. These conventional authentication systems are popular and have proven performance. However, they either require dedicated devices or require user input. WiFi-driven authentication is sensorless and does not require explicit user input. It uses the invisible radio to extract the highly personalized features such as gait patterns for authentication.

WiFi-driven sensorless authentication systems are built on top of gesture recognition systems. Different users will produce different WiFi signal patterns albeit they perform identical gestures. The above intuition serves as the basic principal for WiFi-enabled authentication systems. WifiU [31] leverages the unique gait patterns to identify different users, reporting top-3 recognition accuracy up to 93.5%. And Liu *et al.* [32] and Shi *et al.* [33] proposed a deep learning approach that can distinguish different users from daily activities, both static and mobile, reporting an accuracy of 94% and 91%, respectively. While these authentication systems explore the possibility of authentication using WiFi signal, currently they are feasible only on restricted setups. For instance, WifiU requires the user walks through the same path, and the walk distance is also limited.

IV. RESEARCH CHALLENGES AND FUTURE WORK

A. CHALLENGES

In the previous sections, we have talked about the capabilities of WiFi sensing, which show great potential in smart home automation. However, most of these findings are limited to scientific research. To put them into practical use, several challenges need to be addressed.

1) AVAILABILITY OF FINER GRAIN METRIC

There are two metrics to quantify the signal properties, namely RSSI and CSI. It is easy to access RSSI on most OS platforms. However, RSSI is not so sensitive which limits its application. In contrast, CSI is a much finer grain metric and most of the systems are built on it. Currently, it is feasible to extract CSI only on limited hardware, e.g., Intel 5300 and AR93xx/AR95xx [60]. To make matter worse, the device drive to expose CSI can only work on certain kernel[1] versions of Linux platform [9], [61], which occupy only 0.8% OS market share [60]. Though Android OS is built on Linux, the APIs to extract CSI is not available right now. This limited availability of finer grain metric prevents a widespread adoption of WiFi sensing based applications. We envision that chip vendors can provide APIs to obtain CSI on various platforms in the future.

2) CONFIGURATION-FREE

Assuming that CSI can be easily obtained on different platforms, any applications that leverage CSI signal should be configuration-free which means the systems are irrespective of deployment and are training-free. However, seldom do the literary works satisfy this requirement. The CSI is vulnerable to interferences such as multipath, medium contention, and other electromagnetic noise [50]. These interferences are closely related to the environment settings and the deployment, making the systems configuration-dependent. Some applications may even require strict setup. For instance, keystroke recognition [22] and respiration estimation [40]. In such applications, the transmitter and the receiver are placed quite close so as to achieve high SNR, limiting its practical adoption. The models of training-based methods are not readily applicable across different settings, and additional training would be needed in new locations. So how to make WiFi sensing based systems configuration-free is both challenging and demanding.

3) MULTIPLE PERSON SCENARIOS

Applications that can track, detect or monitor multiple persons are more efficient. However, state-of-the-art gesture recognition and health monitoring systems, mostly are feasible in the case where there is only one person. They fail to work under multiple person scenarios. For instance, the approach [31] to recognize gait patterns can only work when a single user walks through the same paths, limiting its application only to a corridor or narrow entrance scenarios. Respiration estimation in [40] can only work under the presence of two people and can not be generalized to multiple person scenarios. We foresee that applications that can work under multiple person scenarios will emerge in the near future.

4) RESOLUTION LIMIT

WiFi sensing has shown great potential for a myriad of applications. Yet few works have addressed the resolution limits, i.e., the minimal detectable changes or the minimal detectable objects. Some works that leverage customized hardware show the capability of through-wall motion detection [62] and through-wall life sign detection [18], [63], and can even extract gait cycle, stride length, or emotion states [64], [65]. Multiple targets based gesture recognition systems have also been developed on advanced hardware [66]. Huang *et al.* [67] use the reflections from the objects illuminated by the WiFi signal to detect the raw shape. However, using COST devices to achieve comparable performance have yet to be explored.

[1] Some researchers have successfully obtained the CSI on other Linux kernel versions such as 3.5.7, or 2.6.36 [32].

B. FUTURE RESEARCH TRENDS

There are many research directions can be further investigated, and we envision that the following two are of great importance.

1) SECURITY ISSUE

In previous sections, we have presented that WiFi sensing is capable of mining a lot of information, such as locations or even user identity. This may also raise critical security issues as hackers may utilize this information for harmful attack. So anti-attack mechanisms, handling security issue, may arise the interest of researchers in the future.

2) WHEN WiFi SIGNAL MEETS DEEP LEARNING

As we have mentioned before in Section II and Section III-B, CSI, manifesting itself as a matrix, is a measurement record with data stream from different subcarriers and different subcarriers can be regarded as different sensors. This is somewhat like using a sensor array to capture information with a matrix output, which is highly similar to computer vision technology [68]. Therefore, computer vision favored algorithms especially deep learning [69] may be helpful. Deep learning may bring more opportunities for WiFi-enabled systems, which simplifies the deployment and makes the systems configuration-free.

V. CONCLUSION

In this paper, we surveyed state-of-the-art smart home systems and applications based on WiFi sensing. We discussed the principles, capabilities, and limitations of these works. Overall, WiFi sensing is a promising technology for a broad spectrum of smart home applications, which however has yet to be a perfect replacement for conventional sensing mechanism due to various practical concerns. The recent advances in deep learning may offer great help for developing configuration-free systems.

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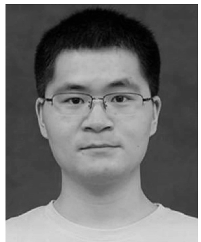

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