Sensing Our World Using Wireless Signals

***Abstract*—In the last decades, consumer-grade wireless signals have rapidly established itself as a powerful medium for sensing. By measuring how the wireless signal is affected by objects and human activities, rich information ranging from gestures to gait patterns and even vital signs can be identified. This article provides an accessible introduction to wireless sensing. It presents the key enabling technology of this exciting research field and its main achievements. It provides a discussion on open issues in the area and potential research directions.**

I. Introduction

Wireless signals, such as WiFi, the radio frequency (RF) and acoustical sounds, have emerged as a powerful medium for information sensing. By measuring how the wireless signal is affected by surrounding objects and human activities, tasks like localization [1, 2], activity recognition [3, 4], and material identification [5–7] could be possible.

The history for using wireless signals for sensing dates back to the 19th century for the discovery of X-rays for object recognition [8] and the development of military radar and sonar systems for tracking large metallic objects in open spaces [9]. These sensing systems, however, have to rely on expensive specialized hardware and be operated by professionals, which thus put them out of the reach of ordinary people.

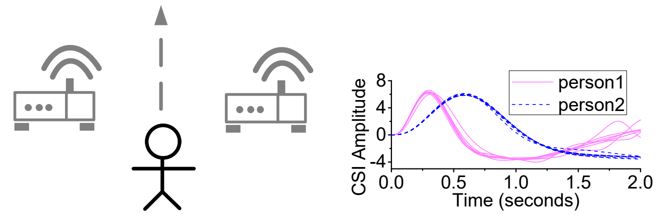
Recently, it has been shown that wireless signals generated by consumer-grade devices such as smartphones and wireless routers can be used to precisely track objects and human activities in an indoor environment. Such technology has the advantages of being low-cost as it requires as few as two wireless routers to operate, not requiring instrumenting the user, being less privacy intrusive compared to other infrastructure-based solutions like video-based solutions [10], and is safer to use on a regular basis compared to other alternatives like X-rays [11]. It is an inexpensive solution for offering sensing capabilities into everyday life, making ever sensing a tantalizing reality.

As we will show in this article, while there are still many challenges ahead, consumer-grade wireless sensing has moved from a research niche to a mainstream activity. This is, in fact, a dynamic field looking at subjects as diverse as smart-home personalization [12] and fall monitoring [13] to emotion detection [14] and vital sign monitoring [15]. In this article we aim to demystify this promising technique, outline the challenges it is facing, and show that this is a trustworthy and exciting research direction.

II. Working Mechanism of Wireless Sensing

A. Working Example

To illustrate how wireless sensing works, consider the gait identification scenario depicted in Figure 1(a). The sensing task in this example is to identify which of a set of known users



(a) (b)

Fig. 1: The working mechanism of wirless sensing. (a) shows a typical set up where two wireless devices are deployed to collect the CSI values when a user walks pass the devices. (b) shows the measured CSI for two individuals, where the resulted CSI amplitudes are relatively consistent for the same person across multiple walks, but are sufficiently different for different people.

has walked pass the scene. Knowing this information allows one to – for example – personalize the light setting of a smart home. Here, two wireless routers (a sender and a receiver) are used to measure how the user's movement affect the wireless channel metric, such as the channel state information (CSI) or received signal strength indicator (RSSI). The idea is that the wireless signal – called "multipath" – will bounce off the wall, furniture, and human body, and the human activity can lead to a subtle change on the attenuation and reflections of the signal; by measuring how the wireless signal is affected by the activity and comparing the measurement against some pre-collected training data, one can infer what activity has been performed and by whom.

Figure 1(b) shows the measured CSI amplitudes of two users in our scenario. In this case, each user walked through our scene five times and the CSI amplitude per walk is shown. This figure suggests that wireless channel metrics can be a useful means for user identification, because the channel metric measurements for the same person is relatively consistent but is sufficiently different for the two people.

Note that although the setup and the sensing method would vary depending on the sensing task and the wireless signal to use, this example shares many of the commonalities of wireless sensing, which demonstrates the underlying working principal of wireless sensing.

B. Choices of Wireless Sensing Signals

As summarized in Table I, a wide range of wireless signals have been employed in prior work for information sensing. These include WiFi, RF, acoustic, LoRa and visible lights, frequency-modulated continuous-wave (FMCW) radar and ultra-wideband (UWB). Signals like WiFi, acoustic, and visible lights are readily available on commercial off-the-self devices

TABLE I: Consumer-grade wireless signals used in prior sensing tasks.

Properties	WiFi	RFID	UWB	Asoustic	LoRa	FMCW radar	Visible Light
Communication Range	35m	10m	10-20m	2-3m	15km	9m-120km	1.4km
Frequency	2.4GHz/5GHz	902.75-927.25MHz	3.1-10.6GHz	17-24KHz	868MHz/903-927.5MHz	24-24.25GHz	380-790THz
Bandwidth	20/40MHz	24.5MHz	1GHZ	–	125/250/500KHz	250MHz	–
Metrics	CSI, RSSI	Phase, Doppler, RSSI	Phase, RSSI	Phase, RSSI	Frequency, Phase, RSSI	Frequency, Phase, RSSI	RSSI
Cost	Low	Low	High	Low	Low	High	High
Modulation	OFDM	OOK	PPM	AM/FM/PM	CSS	FMCW	OOK/CSK/VPPM

(such as smartphones and smart light bulbs), while others like UWB and FMCW often require specialize hardware to operate.

Which signal is best for a sensing task, is the $64,000 question. The answer is, it depends. For examples, while WiFi is almost everywhere, it is limited in the communication range (i.e., 35 meters) and consumes a significant amount of power; by contrast, LoRa supports a longer range (i.e., 15 Kilometers) and needs significantly less power to operate, but it has a much lower bandwidth and is more sensitive to the environmental multipath. Different signals also operate at different frequencies and offer a variety of sensing metrics. Some of the signals like FMCW radar can provide an accurate tracking capability but is more expensive to deploy. It is important to note that there is no "one-size-fits-all" sensing medium, and the choice depends on the trade-off between the precision requirements, the deployment environment, and the budget.

III. Wireless Sensing Applications

Wireless sensing has been demonstrated to be effective on a wide range of tasks from localization onto activity recognition and material identification.

A. Localization

Target localization and tracking are two popular sensing applications. WiFi and radio-frequency identification (FMCW) are the predominate schemes used for this task, due to the low-cost and wide-scale deployment of the schemes. Acoustic signals have also been employed for localization and tracking, thanks to its slow propagation velocity and robustness to environment changes.

Localization can be achieved by using wireless fingerprints or a predictive model. A fingerprint-based approach works by first collecting the wireless fingerprints of a set of carefully chosen locations. During deployment, it compares the measured wireless channel metric (e.g., RSSI or CSI) against the pre-collected fingerprints, and then uses the most-similar fingerprint to infer the location of the target object. Such an approach has a low deployment cost, but its accuracy is susceptible to the environmental change and indoor multipath.

As an alternative, predictive models learn the correlation between the wireless signal characteristics and the indoor locations. Such approaches can be categorized into two groups. The first is to use the arrival-of-angle (AoA) or time-of-flight (TOF) of the wireless signals for location estimation. The second is to exploit the signal energy attenuation for location estimation. Predictive models have the advantage of having a better generalization ability over the fingerprint counterparts, i.e., it can estimate arbitrary locations of the target environment.

However, predictive models are not a panacea and often suffer from hardware imperfections (e.g., it is difficult to obtain an accurate TOF) and multipath effects (which make it hard for obtaining good signal attenuation). They also have the difficulties for determining the target's initial position. Several countermeasures have been proposed to address these issues. These include (i) using pre-collected fingerprints [16], directly modeling the phase differences [17], information obtained at multiple signal frequencies [18–20], or multiple tracking devices [21] to improve the information gain; (ii) using multiple antennas [1, 22] to cancel the multipath effect or directly modeling the multipath profiles [23]; and (iii) leveraging the virtual antenna array to obtain the initial position [2].

B. Activity and Behavior Recognition

Human activity and behavior recognition is another area where wireless sensing has demonstrated great potential.

Some of the early work of the area use multiple transmitters and receivers to construct a 3D lattice of wireless links to identify if there is a human movement and if so what is the user's location. Efforts have been made to use a single device equipped with multiple antennas to build a practical solution. For examples, WiSee [24] was able to send signals from outside a room to track human movements; and WiTrack shows that is possible to recognize hand gestures from signal perturbations. A more recent work illustrates the possibility for using wireless signals for measuring a baby's breathing and heart rate [15]. The idea is that the chest movement caused by breathing would alert the signal reflections, which in turn allows one to capture the breathing event and count the heart rate with enough accuracy. By precisely counting the heart beats, one can even predict a user's emotion [14].

Machine learning based classifiers have been widely used in activity recognition. The effectiveness of such schemes in general depends on the quality of the training data and features for capturing the characteristics of the data. As a result, some of the recent research efforts turn into seeking ways to automatically identify useful features [25] or reduce the human involvements (and thus the cost) for generating high-quality training data [7].

C. Material identification

Target material identification is a key role in our life, many applications would benefit from it, such as detecting concealed weapons and determining food deterioration.

Existing material identification systems such as Radar, X-Ray, CT, MRI and B-scan ultrasonography use special hardware with high frequency, large bandwidth and antenna arrays, which are extremely expensive and usually large in size. Recently, some works utilize the wireless signal to sense the target material. For examples, [5] use the property of wireless signals propagating in liquids to identify the different material, which is the changes of RSS and phase. Similarly, [6] utilizes cheap UWB devices with 1GHz bandwidth to extract the dielectric constant for fine-grained liquid sensing.

D. Target imaging and 3D reconstruction

Target imaging is a new area where has attracted much interest from both the industry and the research community. Traditional imaging systems like Radar, X-Ray, CT employ dedicated hardware with high frequency, large bandwidth and antenna arrays, which are extremely expensive and usually large in size. Hence, some researchers attempt to use RF signals to image a target shape. Tagscan [5] leverages each propagation distance inside a target represents one piece of target width information at one angle, by stitching together the width information at many angles can obtain the horizontal cut image of the target. However, this approach needs a robot with antenna moves around the target, which extremely limits the systems practicability. To deal with this issue, RF-Capture [26] utilizes a FMCW device to reconstruct the skeleton of a human target behind a wall by extracting the signal reflections from human body parts. However, this system exhibits some limitations. For example, it needs target starts by walking towards the device, then it only adopts a simple model for the human body for segmentation and skeletal stitching, which only captures a very coarse-grained target image. To further deal with these problems, RF-Pose3D [7] infers 3D human skeletons by incorporating RF signal and visual stream. It first leverages deep CNN to infer the persons 3D skeleton, and then uses the visual stream to label different target skeleton. Finally, this system can track each keypoint on the human body with a cm-level accuracy.

E. Vibration detection

Vibration detection plays a vital role in many applications, such as malfunction detection in electronic instrument, monitoring the displacement in vehicle, etc. Traditional vibration sensing schemes require dedicated sensors, which are very expensive. And most of them have a limit monitoring area.

To avoid these drawbacks, [27] proposes to utilize commodity RFID to achieve sub-millisecond vibration sensing. In order to magnify tiny vibration signal induced by micro-vibration this paper introduced a simple mathematical methodology to multiplies the vibration amplitude by a constant. Also, they proposed a compressive sensing model to reconstruct the vibration signal to overcome the challenge of detecting high-frequency vibration with a limited sampling rate.

IV. Challenges of Wireless Sensing

This article has by and large been very upbeat about wireless sensing. However, there are a number of hurdles to overcome to make it a practical reality.

Multipath effect: Due to the inherent propagation nature of wireless signals (they can be reflected, refracted and diffracted off surrounding objects), multiple copies of the same signal may reach the receiver with different phase delays and power attenuation. This phenomenon is called the multipath effect. Especially in indoor environments, the ubiquitous multipath effect drastically affects the behavior of the signals, thus makes it challenging to obtain the fundamental information (RSSI, phase, AoA, ToF, etc) for accurate target sensing. While recently literature has proposed to exploit multiple links for nullifying the static noises, or select optimal sub-carriers that are resistant to multipath effect for sensing task, these schemes have poor adaptability to environmental changes. Other attempts for dealing with the multipath effect require a large bandwidth or antenna array, which either require dedicated devices or is difficult to deploy. Therefore, there is a need for effective multipath and noise suppressing algorithms in accurate wireless sensing. We suggest that SAGE algorithm would be the potential candidates to deal with this challenge.

Time asynchronous: To the best of our knowledge, directly using the timestamps reported by commodity devices such as Wi-Fi cards can obtain TOF at a granularity of several nanoseconds, leading to tracking error of a few meters. Although some super-resolution algorithms are applied to obtain finer TOF estimates, the underlying assumption is that all APs (including transmitters and receivers) are time synchronized. This assumption however is unrealistic for commodity Wi-Fi or other devices. Thus dealing with the time asynchronous problem is a crucial as well as challenging issue in wireless sensing. Connecting the transceiver pair by the synchronization line is a effective solution, but it is limited to scenarios where transceivers are closer to each other. Hence, a wireless synchronization scheme is urgently needed.

Deployment issue: To the best of our knowledge, the non-contact sensing performance is highly relevant to the deployment when the transmitter and the receiver are placed separately, due to the presence of Fresnel zones. The optimal transceiver placement would contribute to high sensing accuracy, while an random placement would lead to large amount of blind spots for sensing. So the deployment issue should be taken into account in real applications. Of course, we need to pay attention to an implicit trade-off between improving the sensing accuracy and resolving the inconveniences. Since the optimal deployment is always at the expense of more restrictions, so that brings much inconvenient experience for user. Therefore, it is recommended to choose the suitable deployment according to the specific application, and make a good compromise between practicality and sensing performance.

Transfer problem: Many learning based sensing methods can achieve high accuracy without requiring intensive communication links, and can work with even a single transceiver pair, which ensures low hardware cost and great convenience. However, one major unsolved issue is that the learned patterns can hardly adapt to the changes of environment and time. For long-term or varying scenarios, the sensing accuracy would decline seriously if we still utilize the original patterns, and constant updating patterns comes with a huge training cost. Recent works attempt to solve this problem by deep learning technology that can extract hidden useful features of higher dimensions, while these methods lack theoretical basis. To make sensing more convincing, it is better to combine learning with theoretical models by excavating and analyzing the physical nature of signal changes.

Tiny signal extraction: Some interfaces realize their sensing objective by leveraging the reflected signal caused by the target. Nevertheless, the wireless signal arriving at receiver is always a superposition of direct path and various reflected paths. In many cases, the target reflected signal is quite subtle compared to the signal from direct path and strong reflectors, so it is very challenging to separate the weak component from the mixed signal. Traditional solutions generally suppress undesired paths by prior measurement, while they are still unable to thoroughly attain the desired reflected component. The latest work introduce a new idea that conducts nonlinear frequency shifting to the signal reflected off target, this makes it different from the other interfering signals, thus it can be separated. However, this approach still limited to contact sensing. To achieve tiny signal extraction in more complex non-contact scenarios, we believe that the multiple paths approximate estimation and blind-source separation algorithms can serve as the promising solutions.

Evaluation standardization: Currently, there is no standard set of specifications that can serve as a guide for designing sensing techniques. There is no single wireless technology that is widely accepted as the main technology for future sensing systems. As evident from our discussion on the proposed systems in the previous sections, a number of different technologies and techniques have been used for the purpose. However, most of the systems are disjoint and there is no ubiquitous system that currently exists. This poses significant challenges. Therefore, we believe that there is a need for proper standardization of sensing. Through standardization, we can set the specifications and also narrow down the technologies and techniques that can satisfy the regular evaluation metrics. Furthermore, there is a need for creating a universal benchmarking mechanism for evaluating an sensing system.

Public data sets: In order to facilitate communities to restore the published system and ensure the feasibility of the system, opening data set is becoming a trend in the academic community. However, from the authors' point of view, it may be inconvenient to publish all data sets in a time,due to the consideration of later research extensions. We suggest that a compromise way is to expose source code and some data sets.

V. Future Directions

Wireless sensing constructed around consumer-grade devices have demonstrated its utility as a means of information sensing. It will continue to be used for new and more complex application contexts.

In view of the state-of-arts and practical applications, we expect the future research in wireless sensing to follow two trends. **(i) Towards complex sensing scenarios.** Typical applications include in-body localization, through-wall imaging, sensing of high-speed mobile object (high-speed rail, driverless vehicle, UAV), etc. **(ii) Integrating sensing with communication.** By combining the advantages of sensing and communication, we can achieve more amazing sensing and communication technologies such as cross-medium, cross-protocol, cross-frequency. We believe the potential solutions would focus on combining multiple means (multiple signals, multiple devices, active and passive, model and deep learning) and multidimensional parameter estimation.

VI. Conclusion

This article has introduced wireless sensing methods built upon consumer-grade solutions. After much progress has been made in the last decade or so, wireless sensing is now a mainstream research area and has a large amount of academic interest and papers. While it is impossible to provide a definitive cataloguer of all relevant research, we have tried to give an accessible tutorial to the main research topics, challenges and future directions. Wireless sensing is still at its early stage. There are many challenges ahead, but there are much greater opportunities for creative and high-impact research to be conducted in this exciting direction.

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