Wireless Sensing

***Abstract*—..**

I. Introduction

The development of wireless devices has resulted in numerous wireless sensing technologies which enable a variety of applications such as indoor navigation, smart homes, fitness tracking and security check. In recent years, especially non-contact wireless sensing has attracted much attention from both the research community and the industry, due to its convenience of without instrumenting user's body. Many researches have answered how to identify object's location, shape, material, behavior, etc. The basic idea of these designs is to utilize signal processing to construct a mapping pattern or theoretical relationship between the target information and the signal characteristics.

To turn these designs into practical systems, series challenges need to be tackled. Typically, (i) the defects of cheap devices can lead to nonnegligible error of signal information (phase), (ii) environmental changes can alter the regular signal patterns, and (iii) multi-path effect would greatly reduce the estimation resolution of some fundamental parameters for sensing. These always make the system performance extremely poor. To address these issues, many efforts has been made, including: (i) calibrating the inaccurate phase information through comparing with it with a real value obtained in advance, (ii) canceling background noise using signals from multiple links, and (iii) improving the resolution of parameter estimation by splicing bandwidth or constructing virtual array. Nowadays, with the popularity of artificial intelligence, deep learning technology is gradually integrated into signal processing to extract more complex and effective features for sensing task. This drives great success in wireless sensing applications.

In the rest of this paper, we first review the state-of-arts of wireless sensing. Then we conclude the key challenges of this field and suggest promising solutions for them. Finally, we propose guiding insights into future trends.

II. Various sensing applications

In this section, we first introduce the properties of several signals commonly utilized for wireless sensing. Then we review and discuss the typical wireless sensing applications in recent years.

A. The properties of different signals

Nowadays, many wireless signals are employed for plentiful sensing applications, such as Wi-Fi, RFID, UWB, FMCW radar, LoRa, acoustic and visible light. The specific properties for each signal are shown in Tab I:

From the Tab I, we can see that different wireless signals not only have their own unique properties, but also share the common information including phase, RSSI and frequency. These common information allow them to be applied for sensing, and their own characteristics determine their own befitting sensing scenarios.

B. Typical wireless sensing applications

In recent years, with the emerging of the Internet of Thing (IoT), many wireless sensing applications have been inspired, especially for localization and tracking, behavior perception, material identification, target imaging and vibration detection. In this section, we will present these five mainstream applications respectively. We also discuss the challenges coming with them and corresponding efforts have made.

Localization and Tracking: Target localization and tracking are two most universal and significant sensing applications. Specifically, indoor localization has attracted much interest from both the industry and the research community. Among all the technologies employed for localization, Wi-Fi and RFID are considered as the most promising schemes due to the cheap price and widespread deployment. Furthermore, we can easily access the amplitude and phase information from commercial RFID and Wi-Fi devices. In the following, we will discuss previous indoor localization works, which can be classified into two categories: learning-based and model-based localization schemes.

Learning-based localization: These systems collect received signal strength (RSS) and channel state information (CSI) at each location to build fingerprints for localization, which can achieve a meter-level accuracy. Although these systems are easy to be deployed, their localization accuracies are susceptible to environmental change and indoor multi-path. Furthermore, learning-based localization schemes suffer from labor-intensive offline training.

Model-based localization: For a robust, higher accuracy and low cost system, more and more researches have a trend to explore model-based localization approaches, which can be divided into two categories. The first category of localization systems are based on arrival-of-angle (AoA) or time-of-flight (TOF) estimation, which achieve localization by intersecting multiple AoA or ToF estimates. The second category is energy-attenuation-based localization systems, which establish signal energy attenuation model to calculate target localization. These ideas sound simple, however, there exist some common challenges to make them practical.

(i) *Hardware imperfections.* Due to commercial hardware imperfections, we cannot obtain accurate phase information and accurate time of flight.

TABLE I: Different wireless signals with different properties.

Properties	Wi-Fi	RFID	UWB	Asoustic	LoRa	FMCW radar	Visible Light
Sensing range	5-10m	10m	10m	50cm	15Km	9m-120km	1.4Km
Frequency	2.4GHz,5GHz	902.75-927.25MHz	3.1-10.6GHz	17-24KHz	868MHz,903-927.5MHz	24-24.250GHz(European)	380-790THz
Bandwidth	20MHz,40Mhz	24.5MHz	1GHZ		125KHz,250KHz,500KHz	250MHz	
Information	CSI,RSS	Phase,RSSI,Doppler	Phase,RSSI,Amplitude	Phase,RSSI,CSI	Frequency,Phase,RSSI	Frequency,Phase,RSSI	RSSI
Cost	Low	902.75-927.25MHz	High	3.1-10.6GHz	68MHz,903-927.5MH	High	High
Modulation	OFDM	OOK	PPM	AM,FM,PM	CSS	FMCW	OOK,CSK,VPPM

(ii) *Indoor multipath.* In our indoor environment, there exits rich multi-path effects, which result in the inaccuracy of location parameter estimation and signal attenuation model construction.

(iii) *Uncertainty of initial position.* For the tracking systems, it is difficult to determine target's initial position.

To mitigate the phase error caused by commercial hardware imperfections, a basic idea is to employ a optimization model to calibrate phase information [1]. Alternatively, we can use different frequencies to emulate a very large bandwidth for a high accuracy of time estimation [2]. To eliminate the indoor multi-path effect, on the one hand, we can exploit multi-path to capture multi-path profiles for target localization [3]. On the other hand, by increasing the number of antennas in the array, we can improve angle estimation resolution to identify the line-of-sight (LoS) [4, 5]. Furthermore, one skillful idea is to select clear subcarrier information to establish signal attenuation model [6]. To deal with the uncertainty of initial position, we can leverage virtual antenna array and approximate evaluation method to improve tracking accuracy [7].

In addition, acoustic signal has been widely used for localization and tracking, due to its slow propagation velocity and robustness to environment changes. However, there also exist several challenges that are similar to Wi-Fi and RFID based localization systems.

The first issue need to be tackled is the inaccuracy phase information and unsynchronized time induced by the defects of commercial acoustic devices. A standard solution is to use phase difference for tracking target location [8], another approach is employing multiple device to avoid the time asynchrony [9]. The second issue is the indoor multi-path, which results in inaccuracy of model parameters estimation. To deal with this problem, a typical intuition is to design different modulation for acoustic signal, such as frequency modulated carrier wave (FMCW) and orthogonal frequency division multiplexing (OFDM) [10, 11].

Behavior sensing: Human behavior recognition can enable a wide variety of applications, such as heath care, fitness tracking and sleep monitoring. Specifically, human behavior recognition contains large movement sensing such as postures and gait, and fine-grained movement sensing such as breathing, heart beat and lip language. Similarly to localization and tracking systems, human behavior recognition interfaces can also be classified as learning-based and model-based behavior recognition two categories.

Learning-based behavior recognition: For most irregular behaviors recognition, researches depend on pattern learning (DTW, SVM, KNN and BAYES) [**?**] to deal with it. To ensure the recognition accuracy of systems, we need to answer following questions.

How to design a high-quality feature to remove the impacts of environmental changes and target's velocity? How to effectively label substantial data?

To answer the first question, a intuitive idea is performing transfer learning to design the rubout high-quality feature [**?**]. For the second question, a deep learning can be employed to effectively label substantial data [**?**].

Model-based behavior recognition schemes: These model-based behavior recognition schemes can only be applied to analyze few human behaviors with a specific frequency range, such as walking, jogging, running, breathing and heart beat. These activities can be sensed according to that they can cause signal fluctuates with specific frequencies. To make the system operate well in reality, two typical challenges need to be addressed.

How to extract weak signal such as breathing and heart beat? How to eliminate the interference from the other body parts' activities?

To accurately detect the weak breathing and heart beat signals, an effective solution is to amplify them by exploiting the superposition of multiple paths existing in the environment. The interference activities from other body parts can be filtered out in frequency domain.

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. Hence, there exits some challenges to identify target material with commodity device.

How to eliminate the impact of target's size? How to remove the impact of containers and liquid reflections?

To solve the first challenge, we can design a feature, which only depends on the material type and independent of target size, such as the ratio of RSS change and phase change

[12]. Consider that the liquid containers and liquid reflections have some impacts on the above feature, [13] employs UWB devices with high bandwidth to accurate estimate the time of signal propagation, and use it to remove the impact of containers and liquid reflections.

Target imaging and 3D reconstruction: Wireless signal can reflect off or penetrate through various objects in the environment. Thus researches attempt to utilize this to achieve object imaging.

Reflection-based imaging: Due to the physics of radio reflections, at any point in time, the sensor captures signal reflection from only a subset of the human body parts. [14] identifies human body parts from RF snapshots across time to capture the human figure, as the consecutive RF snapshots can expose different body parts and diverse perspectives of the same body part; However, imaging results are highly sensitive to phase accuracy. Thus [15] proposes a new 60Ghz imaging algorithm, which images an object using only RSS recorded along the devices trajectory, as the RSS measurements of 60Ghz are highly robust against noises in device position and trajectory tracking. [MobiSys2018 LiliQiu] proposes a new Phase Gradient Algorithm called MPGA to remove the impact of hand jitters, compensate phase errors, MPGA can effectively support acoustic imaging in a mobile context.

Occlusion is a fundamental problem in human pose estimation. Thus, [**?**] presents a different approach that extracts pose information from the visual stream, and uses it to label the RF signals for dealing with Occlusion. To estimate the 3D skeletons, we need to use RF signals to extract full 3D skeletons of people including the head, arms, shoulders, hip, legs, etc., and apply the convolutional neural network (CNN) to 4D convolution, but common deep learning platforms (e.g., Pytorch, TensorFlow) do not support 4D CNNs. Therefore, [**?**]leverages the properties of RF signals to performs 4D convolutions by decomposing them into a combination of 3D convolutions performed on two planes and the time axis.

Transmission-based imaging: 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, but stitching them together to create the final image is still challenging, as the starting points of the propagation distances are unknown. [12]discovers two target images estimated by two arrays will align well when the starting points of propagation distances are correctly selected, and thus model the imaging problem as an optimization problem by minimizing the difference of two images estimated from the two arrays.

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, [16] proposes to utilize commodity RFID to achieve vibration sensing. However, the challenges are: how to magnify tiny vibration signal induced by micro-vibration for easier detection? how to detect high-frequency vibration with a limited sampling rate of RFID?

For the first challenge, a simple mathematical methodology is introduced, which multiplies the vibration amplitude by a constant. To deal with the second problem, a compressive sensing model is used to reconstruct the vibration signal so that can achieve sub-millisecond accuracy in vibration sensing.

III. Significant challenges and potential solutions

Multi-path 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 multi-path 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 multi-path effect for sensing task, these schemes have poor adaptability to environmental changes. Therefore, there is a need for robust and effective multi-path and noise suppressing algorithms in accurate wireless sensing. We suggest that beam forming and 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.

IV. Future research trends

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.

V. Conclusion

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