Integrated Sensing and Communication: Enabling Techniques, Applications, Tools and Data Sets, Standardization, and Future Directions

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***Abstract*—The design of integrated sensing and communication (ISAC) systems has drawn recent attention for its capacity to solve a number of challenges. Indeed, ISAC can enable numerous benefits, such as the sharing of spectrum resources, hardware, and software, and improving the interoperability of sensing and communication. In this article, we seek to provide a thorough investigation of ISAC. We begin by reviewing the paradigms of sensing-centric design, communication-centric design, and co-design of sensing and communication. We then explore the enabling techniques that are viable for ISAC (i.e., transmit waveform design, environment modeling, sensing source, signal processing, and data processing). We also present some emergent smart-world applications that could benefit from ISAC. Furthermore, we describe some prominent tools used to collect sensing data and publicly available sensing data sets for research and development, as well as some standardization efforts. Finally, we highlight some challenges and new areas of research in ISAC, providing a helpful reference for ISAC researchers and practitioners, as well as the broader research and industry communities.**

***Index Terms*—Integrated sensing and communication (ISAC) systems, Internet of Things (IoT), radio-frequency (RF) sensing applications, sensing data sets, sensing tools, target modeling, wireless sensing.**

I. Introduction

WITH the advance of information and networking technologies, smart-world Internet of Things (IoT) systems can be enabled by deploying a massive number of smart devices with both sensing and communication capabilities [1]. Smart home, smart manufacturing, smart transportation, and smart healthcare are typical IoT systems [2]–[6]. Closely relevant to IoT, cyber–physical systems (CPS) are referred to the systems that have sensing, communication, computing, and control capabilities [3], [7]. With the support of IoT and CPS, the status of numerous things (also known as, objects) of different types can be tracked, monitored, and controlled. Some typical things to track and monitor include human activities, vehicles, and environmental pollution. As both sensing and communications are essential components to these systems, it is critical to have a joint design to maximize the overall system performance.

Nonetheless, deploying sensors is costly and may not be feasible in some deployment scenarios. Thanks to the widely deployed wireless communication infrastructures, such as mobile/cellular networks and ubiquitous WiFi connectivity, the widely available wireless networks have brought new sensing opportunities, providing a cost-effective infrastructure to enable wireless sensing. While the wireless waveform conveys information to the intended receiver, the same waveform can be used as an illuminator to perform sensing by collecting and analyzing the signals reflected or scattered from the target and the environment.

In terms of technology development, there are growing similarities between communication and sensing systems. A number of hardware modules, such as radio-frequency (RF) front end and analog–digital (A/D) converters, may be shared. In particular, the phased array antennas, consisting of a number of antenna elements, have been recently adopted in millimeter wave (mmWave) communication systems to mitigate high propagation loss and support multiuser communication [8]. The same antenna architecture has been used by multiple-input and multiple-output (MIMO) radar to enable high spatial resolution sensing and multitarget monitoring. In addition to hardware components, some basic signal processing modules can also be shared. Integrating these two functionalities could significantly reduce the overall system cost, device size, and energy consumption.

Generally speaking, there are three design paradigms: 1) sensing-centric design; 2) communication-centric design; and 3) co-design of sensing and communication [9]. In the sensing-centric design, the main functionality of the system is sensing, while communication is secondary; this design can be used for an application not requiring high throughput. In general, radar waveforms are transmitted in the system with information embedded in the radar waveform without degrading radar detection performance. In communication-centric design, the system focuses on achieving high throughput to meet the communication application requirements. Opportunistic sensing can be carried out on the communication waveform reflected or scattered from the objects, from which the channel characteristics can be extracted at the sensing receivers. By monitoring changes in the propagation environment, targets can be detected and tracked. In such a system, throughput and packet error rate are the key

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performance indicators, while the sensing performance in general cannot be guaranteed. In the co-design of sensing and communication, the system is designed by considering both sensing and communication requirements. In specific scenarios, sensing and communication require different time, frequency, or spatial resources. This co-design (also called joint-design or integrated design) can be realized through the configuration of the communication waveform (e.g., allocating sufficient pilot signals to satisfy sensing requirements when carrying out pilot-based sensing). In addition, when sensing and communication have different desired beam patterns, the co-design can be realized by designing the signal covariance matrix or the precoding matrix considering both sensing and communication performance requirements.

At the sensing receiver, which might be different from the intended communication receiver, various sensing sources may be used, namely, the received signal strength (RSS) [10]–[13], channel state information (CSI) [14], or the received waveform directly [15]. Generally speaking, RSS is a measurement that can be easily accessed at the receiver, but it only provides overall received signal power, which is a coarse-grained channel information. Thus, it only supports designated applications and often requires multiple transmitters and/or receivers to form a group to perform the task. CSI offers more detailed information about the channel; instead of a single RSS value, it contains the amplitude and phase information of a set of subcarriers in the orthogonal frequency-division multiplexing (OFDM) system. A number of research efforts on CSI-based sensing have leveraged CSI tools that work with a commodity IEEE 802.11n network interface card (NIC) to collect channel CSI for WiFi-based sensing [14]. The received waveform is the most flexible sensing source, as it provides the raw interaction between the transmit signal and the environment, while more signal processing may be required to extract the channel information.

With enabling techniques, a number of sensing applications have been studied through experiments or simulations. These applications span the domains of smart home applications [16], [17], automotive radar [18], [19], traffic monitoring [20], and environmental monitoring [21], and more emerging applications are being discovered every day, driven by advances in communication, sensing, machine learning, and big data analysis technologies. Depending on the target sensing applications and available sensing sources, various signal processing and data processing techniques can be used to accomplish sensing tasks. Furthermore, to assist integrated sensing and communication (ISAC) system design, both high-fidelity channel model and target model are essential. These models enable the evaluation of more complicated scenarios when the experiment is challenging to set up and configure. For instance, to achieve ubiquitous sensing and reliable sensing, sensing tasks could involve numerous sensing entities, target nodes, and various motion patterns. An accurate channel model can provide a viable means to obtain more realistic results and identify potential issues that must be resolved.

The significant contributions of this article are as follows.

1) We explore the enabling techniques that are viable for ISAC, including transmit waveform design, environment modeling, sensing source, signal processing, and data processing. We also discuss emergent applications, including human activities, target localization and tracking, and others.
2) We provide descriptions of some prominent tools used to collect sensing data and publicly available sensing data sets. For the toolsets, we detail the operating frequency band, the use of these tools, and the generated data format. Regarding the sensing data sets, we list their intended applications and data collection details and outline where and how to find them. In addition, we review some standardization efforts on ISAC, such as IEEE 802.11bf.
3) We review the technological advancement of ISAC and outline challenges and topics that need further research, including collaborative sensing, sensing-assisted communication, software-defined networking (SDN) and edge computing-enabled RF sensing, cross-component and cross-layer design and optimization, channel and target models, machine learning and big data analytics for wireless sensing, and security and privacy.

Several survey papers exist on the topics of radar sensing and communication [14], [22]–[25]. For example, Liu *et al.* [25] reviewed the progress of research on radar-communication coexistence and dual-functional radar-communication (DFRC). Hassanien *et al.* [23] focused on the radar-centric system and presented techniques to embed information into radar signals (i.e., beam pattern modulation, index modulation, and fast time modulation). Feng *et al.* [22] reviewed joint radar and sensing communication from both military and commercial applications and presented different levels of the integration of sensing and communication, such as coexistence, cooperation, co-design and collaboration, and the existing works in these categories. Ma *et al.* [14] conducted a survey on CSI-based WiFi sensing. Likewise, Liu *et al.* [24] focused on human activities detection and estimation application and reviewed RSS-based, CSI-based, frequency-modulated continuous-wave (FMCW)-based, and Doppler shift-based techniques.

In contrast to these existing survey papers, our survey is not limited to a particular radio technology. We instead provide a comprehensive survey on the key enabling techniques (transmit waveform, environment modeling, sensing source, signal processing, and data processing) used for diverse applications that span a variety of categories, such as detection, recognition, localization and tracking, parameter estimation, and others. Viable tools and data sets are new areas to explore, and standardization efforts are reviewed. Challenges and a body of new research directions are presented as well.

The remainder of this article is organized as follows. In Section II, we review the key enabling techniques of ISAC. In Section III, we introduce emergent applications that can benefit from ISAC. In Section IV, we review the publicly available tools and data sets. In Section V, we review some

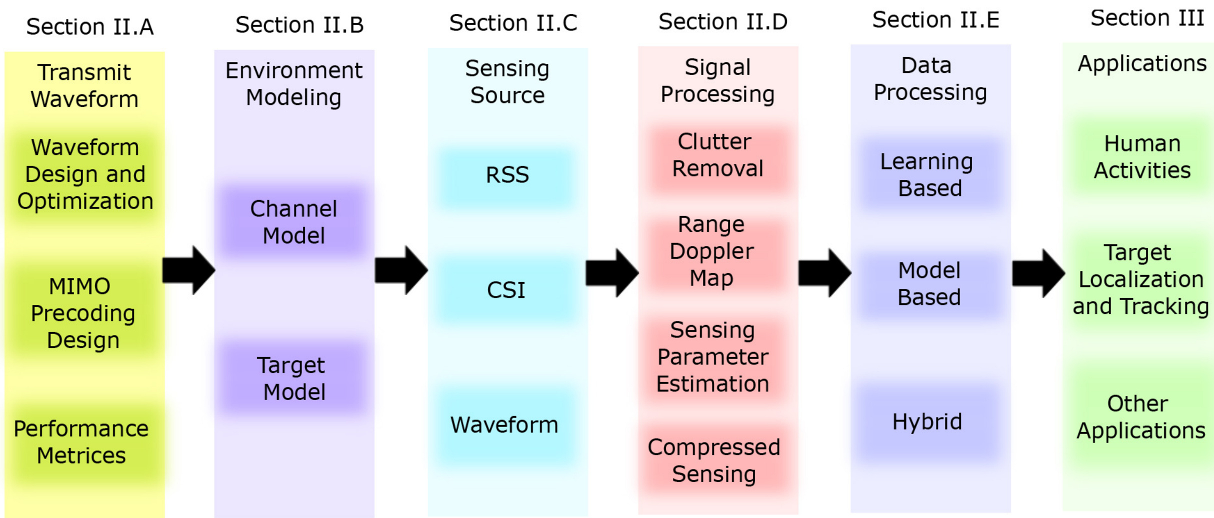

Fig. 1. Enabling techniques and applications.

standardization efforts on IEEE 802.11bf. In Section VI, we outline the challenges and highlight areas of future research. Finally, we conclude this article in Section VII.

II. Enabling Techniques

There are a number of enabling techniques that are viable for ISAC systems. Fig. 1 shows the key techniques, including transmit waveform, environment modeling, sensing source, signal processing, and data processing.

A. Transmit Waveform

The goal of ISAC systems is to use a single waveform to perform communication and radar functionalities simultaneously, optimizing spectrum utilization, enabling hardware reuse, and reducing power consumption. The transmit waveform design is thus a fundamental aspect of an ISAC system. We discuss three different waveform design paradigms: 1) radar-centric design; 2) communication-centric design; and 3) joint waveform design [26], [27], to take into consideration both communication and sensing requirements to support ISAC. We then review the MIMO beamforming techniques for an ISAC system with multiple transmit and/or receive antennas to achieve MIMO communication and MIMO radar functionalities at the same time. Finally, we list the most commonly used performance metrics used in the waveform design along with their tradeoffs.

1) Waveform Design and Optimization: The existing waveform design can be categorized into the following three classes.

Radar-Centric Waveform Design: This type of waveform is adopted in a system in which the main functionality is to carry out sensing while communication is the secondary functionality (e.g., embedding data in the radar waveform for data transmission). To facilitate communication using radar-centric waveform, some commonly used methods are beam-pattern modulation, index modulation, and fast-time modulation [23]. As all aforementioned methods are low-rate modulation, the communication data rate in these systems is generally low compared to the occupied bandwidth. For example, in beam-pattern modulation, the amplitude or phase of the radar beam is modulated based on the transmitted information. Amplitude modulation is applied to the spatial sidelobe (i.e., by changing the amplitude of the sidelobe according to the transmitted information). Phase modulation can be applied to the main beam since it does not affect the radar radiation pattern; it controls the phase of the transmitted beam pattern and embeds the communication information in the phase changes. In addition to beam pattern modulation, index modulation embeds information in the transmission parameters corresponding to the index from a set, such as a waveform ID from a set of available waveforms, frequency hopping codes, or the antenna IDs in an antenna set. Fast time modulation divides the radar pulse into subpulses and uses each subpulse to transmit information, leading to improved communication data rate with minimal detriment to radar performance.

Communication-Centric Waveform Design: Unlike traditional radar waveform using pulse or chirp signal, in order to provide high throughput, a continuous waveform is used for data transmission. Some commonly used communication waveforms are OFDM-based waveform that has been adopted in 4G/5G cellular and WiFi standards. Communication signal has its performance limitations for sensing. For example, it, in general, has a high peak-to-average power ratio (PAPR). Moreover, the cyclic prefix (CP), which is used to avoid intersymbol interference (ISI) in the communication system, could introduce Doppler ambiguity in radar sensing [28]. Furthermore, the information-carrying waveform can lead to high sidelobe gain, which, in turn, reduces the detection dynamic range. Thus, additional signal preprocessing should be in place to address these issues.

Some existing works have been conducted to evaluate the sensing performance utilizing communication waveforms. For example, Sturm and Wiesbeck [28] studied the suitability of single-carrier (SC) signals with spectrum spreading and multicarrier waveforms for joint sensing and communication. They explored the radar signal processing algorithms to realize the sensing functionality using these waveforms. Simulation results reveal that the OFDM waveform has some advantages, such as a larger dynamic range and easier relative velocity estimation over the SC spread spectrum. Fink and Jondral [29] compared the radar functionality of OFDM waveform and chirp sequence in terms of detection accuracy, maximum detection range, required resources, and signal processing. Their analysis demonstrated that both waveforms have the same two-dimension detection accuracy (i.e., range and Doppler) and have similar radar processing demand by configuring the waveform frame structure accordingly, while OFDM is more suitable for simultaneous communication and sensing with additional signal processing effort to remove CP and the dependence on modulation symbols.

Likewise, Nguyen and Heath [19] studied multitarget detection with IEEE 802.11p short-range communication waveform, which is based on the OFDM frame structure defined in the standard. In particular, estimation of signal parameters via rational invariance techniques (ESPRIT), an extension of the multiple signal classification (MUSIC) algorithm, was adopted to detect multiple targets simultaneously. In their study, the range ambiguity, velocity ambiguity, and their relationships with the system parameters were identified (e.g., the range ambiguity is inversely proportional to the subcarrier spacing; whereas the velocity ambiguity is inversely proportional to the carrier frequency and the detection sampling interval). Also, range resolution improves with increasing bandwidth, as does velocity resolution with increasing carrier frequency and observation window. The authors demonstrated that their designed scheme can detect the presence of multiple targets in the environment. In their scheme, the channel response at a given time slot across the subcarriers and the channel response at a given subcarrier over multiple time-slots are used to estimate the range and the velocity, respectively.

Interestingly, OFDM-based WiFi waveform, adopted in commercial WiFi devices, has also been widely used to demonstrate the capability of human activity sensing [30]–[36]. For example, Wang *et al.* [30] used WiFi signals to recognize humans based on fine-grained gait patterns, whereas Ali *et al.* [34] used WiFi signals to recognize keystrokes. Likewise, Cao *et al.* [35] and Abdelnasser *et al.* [36] considered WiFi signals for fine-grained writing recognition and gesture recognition, respectively.

Joint Waveform Design: To use a single waveform to transmit data and perform radar sensing simultaneously, the waveform should be able to accommodate the radar sensing requirements, such as range and velocity estimation accuracy, as well as communication requirements, such as reliability, throughput, and latency, while satisfying power consumption requirements. To fulfill these requirements, one approach is to carefully configure the system parameters (e.g., frame length, pilot size, and pilot transmission frequency). In this context, Braun *et al.* [37] studied the application of vehicle-to-vehicle (V2V) communication at 24-GHz frequency band, where the OFDM waveform is used for range and velocity estimation. The authors also discussed OFDM modulation parameter selection (for example, carrier spacing, number of subcarriers, and frame length) to meet range and velocity resolution requirements. Moreover, the minimum required signal-to-noise ratio (SNR) to perform communication and radar detection is studied in this work, and the effective data rate is evaluated based on the selected OFDM frame structure.

Likewise, Kumari *et al.* [38] proposed a preamble structure to improve the accuracy of velocity estimation in a mmWave WiFi system. In the proposed design, the preamble can be transmitted nonuniformly, and by using these preambles, several virtual preambles can be reconstructed to facilitate vehicle velocity estimation, with a small reduction in communication throughput. This approach jointly optimizes radar and communication performance by finding the minimum number of frames required to meet the radar Cramer-Rao bound (CRB) requirements or the optimized frame locations to minimize the CRB if the number of frames is given. Ozkaptan *et al.* [39] used OFDM waveform, especially pilot symbols, for mmWave automotive radar operating at 76–81-GHz spectrum band. In their work, a joint optimization problem utilizing the OFDM parameters (for example, pilot subcarriers and power allocation for pilots) is formulated to maximize radar performance or communication capacity subject to the constraints from other functionalities.

Finally, some existing work studied the ISAC system using combined independent communication waveforms and radar waveforms [40], [41]. In these studies, a monostatic radar setup with multiple transmit antennas is used to communicate with multiple users and transmit the same waveform as the probing signal to radar targets simultaneously, as a combination of a MIMO communication system and a MIMO radar system. By adding the radar waveform, the spatial degrees of freedom (DOF) of the MIMO radar could be increased. When only communication waveform is used, the spatial DOF of the MIMO radar is limited to the number of communication users [40], which in turn distorts the radar beam pattern, especially when the number of users is much fewer than the number of transmit antennas. On the same topic, Hua *et al.* [41] studied whether the dedicated radar/sensing signal is necessary to improve the beampattern matching performance. The study suggests that adding radar waveform to the communication waveform improves sensing beampattern matching performance in general; however, it brings more benefit when the receiver can perfectly cancel the interference from the sensing signal.

2) Beamforming Design: The ability to form additional transmit beams for target sensing is essential when the target is outside the illumination coverage of the communication beam. Thus, the MIMO system, being capable of forming multiple directional beams as shown in Fig. 2, should be considered to enable multiuser communication and multitarget sensing simultaneously.

The beamforming design problem can be formulated as a joint optimization problem between communication and sensing. Depending on the sensing and communication objectives and requirements, the goal is to achieve *pareto* optimality of the system. On this topic, Liu *et al.* [42], [43] studied a simultaneous cellular communication and sensing scenario,

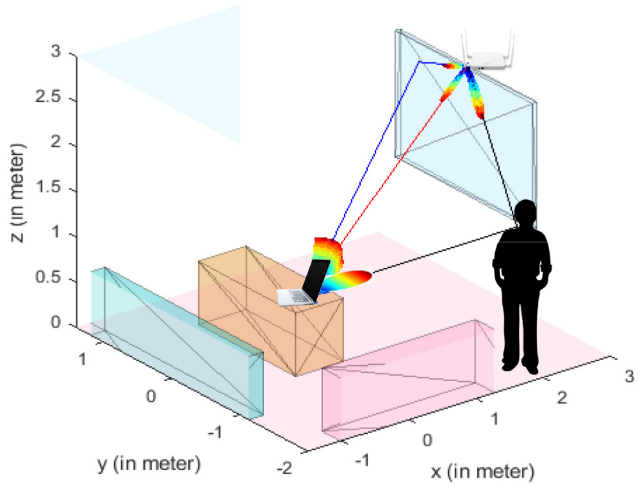

Fig. 2. MIMO enabled simultaneously communication and human sensing. Additional beam is formed for sensing when a human target is outside of communication beams' coverage.

in which a transmitter, equipped with multiple antennas, transmits information to multiple users while detecting several radar targets at the same time. Here, the objective of the communication model is to maximize the achievable sum-rate by minimizing the multiuser interference (MUI) while the objective of the radar model is to design a desired beam pattern by formulating the correlation matrix of the probing signal. In particular, in [42], the tradeoff between the radar and communication performance is tackled by optimizing the weighted summation of communication and radar individual objective functions, and the weights can be adjusted to balance the radar or the communication functionality accordingly. Likewise, Liu *et al.* [40] investigated how to leverage the MIMO paradigm to achieve sensing and communication simultaneously. In their study, a combined waveform, which consists of uncorrelated radar waveforms and communication waveforms, is transmitted through multiple beams toward multiple users and targets. It is worth noting that the uncorrelated radar waveform for each antenna element is generated using pseudorandom coding. In order to jointly design the radar precoding matrix and communication precoding matrix, the optimization problem is formulated as a radar beam pattern matching problem under the constraints of the minimum required signal to interference and noise ratio (SINR) at each user and the per-antenna power constraint.

The advancement of mmWave communication technologies brings unique opportunities for supporting sensing applications with more stringent requirements. The large bandwidth used in the mmWave communication system has the potential to improve the sensing resolution in terms of range. Also, the usage of a phased-array antenna offers more DOF to support more users and monitor more targets simultaneously. To this end, Liu and Masouros [44] designed a hybrid A/D (HAD) precoding matrix to communicate to a single user device with multiple antennas and simultaneously monitor multiple targets of interest. The design goal is to balance the tradeoff between communication and target sensing. In particular, for communication, the goal is to best match the hybrid beamforming matrix to the digital beamforming matrix of a full-digital transmitter, while, for the sensing, the goal is to best match the hybrid beamforming pattern to the desired radar beam pattern. The objective function is formulated as the weighted sum of the minimum squared error (MSE) between the full digital precoding matrix and the HAD precoding matrix, as well as the difference between the HAD precoding matrix and the desired radar beamforming matrix multiplied by a unitary matrix that does not change the desired beam pattern. A nonconvex optimization framework was developed to solve the optimization problem. Moreover, to effectively support simultaneous multiuser communication and sensing, Liyanaarachchi *et al.* [45] designed both the transmit and receive beamforming by optimizing the transmit beamforming so that the beamforming gain in the direction of the target can be maximized while reducing the interuser interference. At the receiver, analog combining weights of each subarray are selected to maximize the receiver beamforming gain in the target direction and suppress the self-interference from the transmitter due to a full-duplex configuration.

There are several existing works on precoding design to leverage the IEEE 802.11ad system for vehicular radar. Since IEEE 802.11ad employs analog beamforming to form a highly directional beam to support a single data stream, the field of view (FOV) of the beam can be limited. In order to increase the FOV, it is possible to exploit sector-level sweep (SLS) during the beam training phase [46]. During the SLS step, the transmitter and the receiver exchange training frames over an exhaustive set of predefined directions (i.e., antenna sector) to find the sector pair that provides the best signal quality; the training frame can be used as the probing signal for sensing. The FOV can alternatively be expanded by activating only a subset of phased-array antennas [47], effectively widening the beam by shortening the aperture length. In this case, a random subset of the transmitter antennas is selected, the main beam can be steered toward the communication receiver, and the random grating beams can be obtained for sensing.

3) Performance Metrics: The waveform design or MIMO precoding design problem, in general, can be formulated as a joint optimization problem to maximize an objective function for communication or sensing while satisfying certain constraints with respect to resources and the deployment. To study the tradeoffs between communication and sensing performance, a set of performance metrics can be used.

1) *Communication Performance Metrics:* The examples of communication metrics include channel capacity [39] that describes the amount transmitted signal carried in the received signal, MUI [42], SINR [40], as well as the difference between the hybrid beamforming precoding matrix and the full digital precoding matrix [40] to measure the communication perform degradation due to hybrid beamforming.
2) *Sensing Performance Metrics:* There are some typical metrics for quantifying the performance of sensing. The examples include mutual information for sensing [48] that describes the amount of channel information carried in the received signal, Cramer–Rao lower bound

(CRLB) [38], a minimum variance for an unbiased estimator, or difference between generated beam pattern and radar desired beam pattern [43]. Also, detection probability and false alarm probability can be used for sensing applications. For example, Xu *et al.* [48] derived radar mutual information between the target channel and the received signal to evaluate the radar performance given a known transmit signal.

B. Environment Modeling

1) Channel Model: A significant portion of sensing research efforts have been carried out using commercial WiFi devices or software-defined radio (SDR), especially in the human activity sensing, mainly in the sub7-GHz frequency band [24], [50]. Although commercial devices and testbeds are closer to reality, the study can be limited by the supported waveform and hardware configurations. Thus, to fill the gap, simulations that use a channel model to represent the physical environment are required. An accurate channel model is essential to study the fundamentals of joint sensing and communication and can be used to provide a performance baseline for such systems.

The transmit signal reaches the receiver via multiple propagation paths. In addition to the direct path, the signal also interacts with the environment. Multiple scaled and delayed copies of the transmitted signal arrive at the receiver after reflecting from macroobjects (much larger than the wavelength) and diffracting from microobjects (comparable to the wavelength). Other factors such as surface roughness also contribute to the received signal. In an ISAC system, the modeled channel usually contains the target-related propagation path (that is, the propagation paths interfered by the target) and the target-unrelated propagation paths (that is, the propagation paths interfered only by the surrounding environment). Conventional stochastic channel models, such as tap delay line (TDL) and cluster delay line (CDL) [51], can be adopted to model target-unrelated propagation paths. Nevertheless, they lack spatial consistency, which is essential to model the impact of the environment on the target sensing. In contrast, hybrid or quasideterministic channel models, such as QD model [52] and QUADRIGA [53], can capture spatial consistency with much lower computation complexity than deterministic models using ray tracing or ray bouncing.

2) Target Model: When the transmit signal reaches the target, it will scatter into all directions, and the scattered energy from the target is proportional to the power of the incident waveform illuminated on the target. The ratio of the scattered power density to the incident power density is denoted as the radar cross-section (RCS) [54], which can be obtained from real-world measurements. Note that the RCS value depends on the scattering characteristics of the target. Besides modeling the target's RCS, the ability to describe the spatial–temporal evolution of the channel due to the motion of the target is essential for micro-Doppler analysis. To this end, several human models have been adopted in the existing literature. For example, Li *et al.* [55] proposed a primitive-based autoregressive hybrid (PBAH) channel model for joint sensing and communication. In the primitive-based channel model, human is modeled using multiple body parts [56], having sphere, cylinder, or ellipsoids shapes. The position of these body parts changes over time by following the Thalmann model [57]. For each body part, radar reflection can be computed using a primitive-based method and added at each simulation step to obtain the target model. Moreover, the target unrelated propagation paths are generated based upon the QD channel model, while the time evolution is taken into account.

In addition, Vahidpour and Sarabandi [58] studied the use of mmWave radar for detecting human and human carrying objects. This work modeled the radar backscatter of walking humans using the polarimetric model, which leverages the geometric optics (GO) and physical optics (PO) models to compute the electric and magnetic currents on the body surface at W-band (75–110 GHz). Likewise, Gürbüz *et al.* [59] proposed a human model composed of 12 points, where each point represents a body part, and the point trajectories provide motion information. The simulations include the human target, the ground clutter, and some nonhuman objects to emulate the realistic environment. In their model, the human head is modeled as a sphere, and the other body parts are modeled as cylinders. Clutters, as reflections from nontarget objects, are modeled using the colored Gaussian model.

Some efforts have been made [60], [61] to introduce the human target notion into the QD channel model and include the target-related rays (T-rays) through the raytracer, as shown in Fig. 3. This proposed QD channel model provides consistency in both spatial and time domains to enable a realistic micro-Doppler description; however, it cannot represent the sensing uncertainty that arises due to higher order reflections from the walls and body parts and target RCS is yet to be modeled. This human target modeling is an ongoing effort, and several channel measurement campaigns have been conducted by NIST to fine-tune this model [62], as shown in Fig. 4, including measuring and modeling the RCS values for the scattering centers.

For nonhuman sensing applications such as automotive radar, a single-reflection point target model has been widely used while analyzing the system performance [63]. In a recent study, Duggal *et al.* [64] verified through the real measurements that the target involved in the automotive radar, including cars, bicycles, and pedestrians, should be modeled as an extended target described by a number of modeling parameters, such as target size, shape, and components. Also, PyBullet [65], an open-source software development kit (SDK), was used to generate the target motion data for cars and bicycles, which was further integrated into the primitive modeling technique [66] to simulate radar return signals based on electromagnetic models. It is worth noting that the pedestrian animation data was obtained from Sony America [67] instead of using the PyBullet SDK.

C. Sensing Source

The presence of the target and its movement can interfere with the propagation of wireless signals. While in a communication system, the channel/environment effect is estimated and

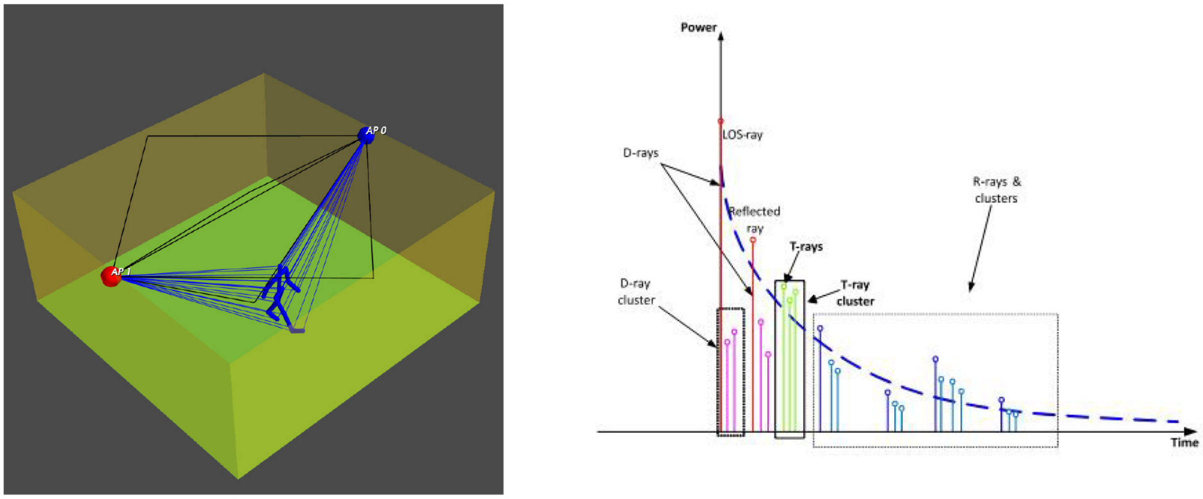

Fig. 3. Channel modeling with human target (a) human walking simulation and (b) channel impulse response consisting of deterministic rays (D-rays), T-rays, and random rays (R-rays).

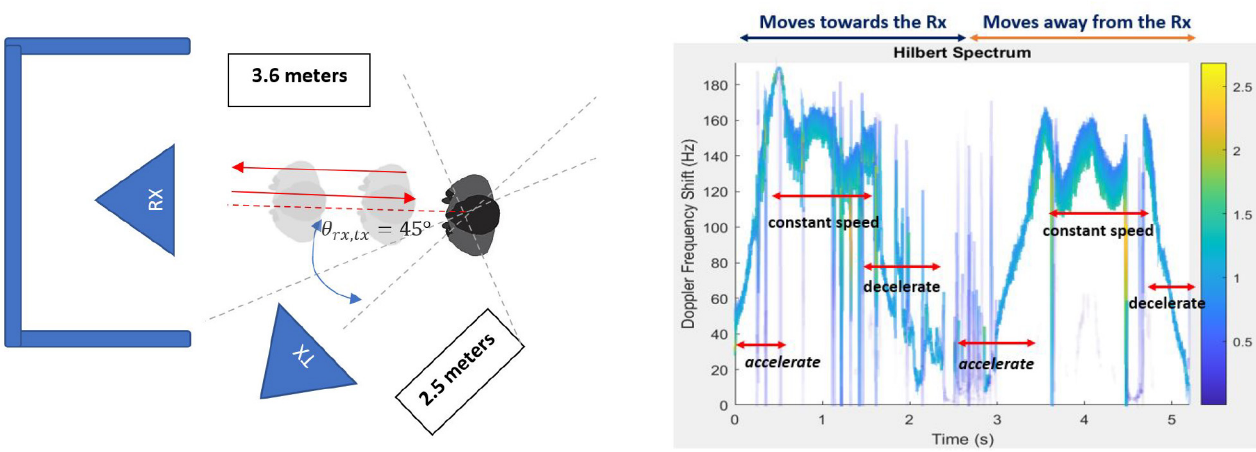

Fig. 4. NIST channel measurement campaign. (a) Human tracking using NIST 28-GHz phased-array channel sounder. The sounder extracts the (co-polarized and cross-polarized) complex amplitude, delay, and azimuth/elevation AoA of resolvable paths scattered from the human body, in real time and with high precision. In this setup, the human object walks directly toward and then away from RX, following the red arrows. (b) Hilbert spectral analysis of the extracted propagation paths. The main frequency components correspond to the motion of the human torso. The human motion patterns from the spectral analysis, including the regions of acceleration, relative constant speed, and deceleration, match the measurement setup in Fig. 4(a).

compensated (e.g., multipath and Doppler effect) so that the received signal can be decoded reliably, sensing functionality generally exploits the channel information embedded in the received signal for target detection and sensing parameter estimation. To perform sensing, we can use the following typical forms: the received signal directly, RSS information, or CSI. The benefit of leveraging RSS and CSI for sensing is that both RSS and CSI can be easily accessed at the receivers [68]. Among these three forms, the received signal provides the most primitive information, so it may require more signal processing, computational and network overhead, and custom hardware support.

1) RSS: RSS is a physical layer measurement commonly used in wireless systems, determined by the propagation loss between transmitter and receiver, and has been widely used in indoor localization [10], [11]. Both device-based localization [10] and device-free localization [69] have been studied in the existing literature. For RSS-based localization, multiple communication links are required to collect the radio signature from each target at each location. In addition to localization, other applications, including room occupancy monitoring [12] and breathing finding [13] using RSS, have been investigated in wireless sensor networks. Regardless of its easy accessibility, RSS is highly sensitive to signal interference and shadowing effects. It also requires a sensor network, which consists of multiple transmit and receiver nodes to perform the task, and often requires RF calibration (for example, for the RSS-ranging conversion).

2) CSI: CSI is the complex gain per subcarrier in an OFDM system, and is available on some commercial devices. For example, Intel 5100 NIC [70] and Nexmon [71]—a firmware patch—are used to extract CSI for OFDM-based WiFi systems. To obtain CSI, the propagation channel is estimated using the known training pilots in the communication waveform. The channel frequency response (CFR) at each subcarrier is then computed and reported. By collecting the

CSI variation over time, which has more fine-grained channel information than RSS, target motion and its pattern can be detected and recognized. In this context, Ma *et al.* [14] conducted a comprehensive survey on WiFi sensing with CSI, where the related signal processing techniques, algorithms, and applications are reported. Unlike RSS, CSI has been used in broader applications, including target detection, human activities recognition, and target parameter estimation, such as range, direction and/or velocity estimation [14]. Some representative applications include human counting [72], human identification [30], human tracking [50], activity recognition [31]–[33], gesture recognition [34]–[36], and breathing monitoring, among others. For example, to support the application of recognizing fine activities (gesture recognition, stroke, etc.), Duan *et al.* [31] first used CSI amplitude variation and leveraged the backpropagation neural network algorithm to classify driver's actions using commodity WiFi product. Ali *et al.* [34] also studied key stroke recognition using CSI; however, in order to achieve better recognition performance, the data were collected in a stable and controlled environment. Likewise, Cao *et al.* [35] presented a device-free WiFi signal-based writing system, where the CSI values from commercial off-the-shelf (COTS) WiFi devices are collected and subsequently used as input in the detection algorithm.

3) Waveform: As an alternative to CSI and RSS, waveforms reflected from the target have been directly used for radar sensing. In principle, basic radar processing relies on signal correlation and frequency analysis over time to estimate delay and Doppler frequency shift (also known as, Doppler), which translate to target range and velocity, respectively. Two types of waveform have been used to perform waveform-based sensing: one based on radar waveform and one based on communication waveform. For the first type, the traditional radar waveform such as FMCW has been used to carry out sensing tasks, such as elder fall detection [73] and multiple persons tracking and identification of their locations in indoor office building environments [74]. In terms of communication waveforms, Huang *et al.* [75] investigated how to use multipath reflections of OFDM-based WiFi signals to construct the image of tracked objects and demonstrated a prototypical system to localize static human beings and metallic objects. Likewise, Pu *et al.* [15] introduced a gesture recognition system, which uses WiFi signals to carry out human gesture recognition for whole-home sensing. In their study, a prototype system based on a universal software radio peripheral (USRP) was leveraged to demonstrate the feasibility of sensing (i.e., recognizing nine gestures with an accuracy of over 90 %) in office and apartment environments.

To employ communication waveform for sensing, one common practice is to use the pilot signal, which is known at the receiver [39], [63]. For instance, Kumari *et al.* [63] leveraged IEEE 802.11ad-based radar at the 60-GHz unlicensed mmWave band for joint vehicular radar and communication. This work utilizes the preamble in a data frame defined in IEEE 802.11ad SC mode for frame detection, time synchronization-based range estimation, and frequency synchronization-based velocity estimation. Similarly, Ozkaptan *et al.* [39] studied sensing using the pilot signals in an OFDM waveform. The other method is to use the whole waveform, including the data frame, to perform sensing. In this case, we have a longer sensing waveform compared to pilots only, which can potentially increase the detection range. However, the transmit data symbols are unknown, especially when considering a radar bistatic configuration. Direct sensing using this waveform leads to poor correlation properties or high computation complexity if using more advanced signal processing techniques to reconstruct the channel [76]. In order to use the whole waveform, the data symbol can be obtained either by decoding the information at the communication receiver or directly passed from the transmitter if the transmitter and the receiver are co-located. With the prior knowledge of transmitted symbols, the effect of the data symbol can be removed from the received signal to acquire the channel response [77].

D. Signal Processing

We now introduce some commonly used sensing signal processing techniques.

Clutter Removal: For sensing applications, the objective is to detect the targets by observing the impact of the target on the wireless signal propagation over time. However, in a rich scattering environment, beyond the signal scattered from the target, the received radio signal can also contain unwanted echoes from the objects in the environment, including the direct signal from the transmitter to the receiver. By containing very little information regarding the target, these unwanted signals can interfere with the target sensing and degrade sensing performance. These nontarget-related propagation paths are referred to as clutters, originating from static objects present in the environment (for example, trees and buildings in the outdoor environment and walls and furniture in the indoor environment).

Several clutter removal techniques have been proposed for different sensing scenarios and deployments. For example, Dokhanchi *et al.* [78] leveraged the spatial precoder design to steer the illumination signal toward the target so that the signal-to-clutter ratio (SCR) can be improved. Background subtraction has also been proposed [79]–[81] to remove the static clutter by averaging the inputs over a time window and subsequently subtracting the average value from the inputs. Similarly, Huang *et al.* [82] designed the scheme to simply remove the direct current (DC) component in the range-Doppler map from each range bin in order to suppress the clutter. Storrer *et al.* [81] designed the delay-line canceller algorithm, which engages a filter to keep the difference between two consecutive channel estimation coefficients so that the impact of static objects can be eliminated. In addition, the work in [81] evaluated and compared several computationally intensive clutter removal algorithms, including the extended cancelation algorithm, which removes clutter from the received signal by projecting the received signal to a subspace orthogonal to the clutter space.

Range-Doppler Map: Range-Doppler map is a widely used technique in radar processing, which leverages matched filter by correlating the received waveform with the transmitted

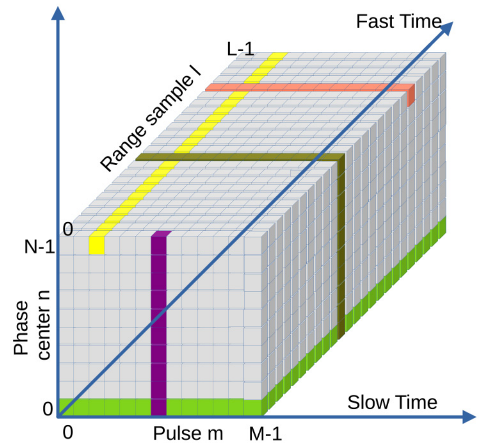

Fig. 5. Three-dimensional (3-D) radar processing data matrix [54, Fig. 3.8].

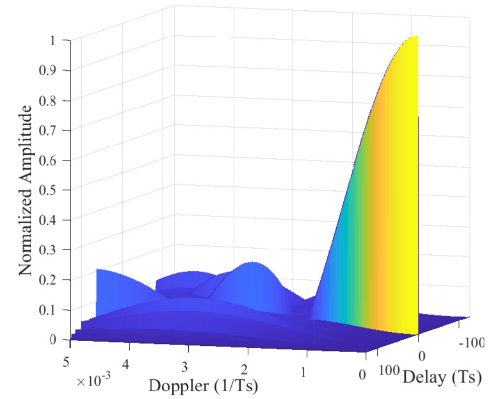

Fig. 6. Ambiguity function of a 128-length complementary Golay sequence.

waveform. A range-Doppler map contains a fast time axis and a slow time axis as shown in Fig. 5. Each slow time instance contains one received sample collected for one radar pulse, or equivalently one data processing unit (containing pilot signal and/or one data frame) in a communication waveform. Different fast times correspond to different propagation delays or ranges. On the slow time axis, the same collection process is repeated over multiple pulses with pulse interval T_{PRI}. When the system has multiple receiver channels due to multiple antenna elements, the 2-D data matrix can be stacked along these receiver channels to form a 3-D data matrix, as shown in Fig. 5. Through the correlations along the fast time axis, the target's delay can be extracted and converted to the signal propagation distance from the transmitter to the target and the receiver. Subsequently, by fixing the range bin along the fast time axis and performing fast Fourier transform (FFT) along the slow axis for a given coherent process interval (CPI) T_{CPI}, the Doppler feature can be extracted for each range bin, which corresponds to a fixed delay bin. In addition, beamforming can be applied to the received channels to retrieve the spatial properties of the target.

The fast time sampling rate determines the range resolution. For example, with a monostatic sensing deployment (i.e., transmitter and receiver are collocated), the target range resolution can be computed as $\Delta r = (cT_s/2)$, where c denotes the speed of light and T_s is the sampling interval. For a fixed range, the slow time discrete-time Fourier transform (DTFT) extracts the Doppler information of the targets at that range. The maximum unambiguous range r can be computed as $r = (cT_{\text{PRI}}/2)$. The maximum unambiguous frequency shift $f_{D_{\max}}$ along the slow time axis is determined by the pulse repetition interval, and can be computed as $(1/2T_{\text{PRI}})$. Moreover, the Doppler shift resolution Δf_D depends on CPI T_{CPI}, and can be computed as $([f_{D_{\max}} \times T_{\text{PRI}}]/T_{\text{CPI}})$. For gesture recognition, the study in [83] extracted the features of the moving hand using the range-Doppler map, range profile, Doppler profile, and spectrogram, which describes the signal spectrum over time. On the other hand, Ozkaptan *et al.* [39] coherently integrated the reflected pilot signal in an OFDM system through the matched filtering to estimate the range and velocity of the target. Also, Gürbüz *et al.* [59] leveraged synthetic aperture radar (SAR) techniques to obtain the range-Doppler map. This work further computes the spectrogram by taking the FFT over short and overlapped time segments and stacking them together to detect torso movement and stride length and the RCSs of different body parts.

Since these techniques are based on the matched filtering results, the range and Doppler estimation performance can be greatly impacted by the waveform correlation property (i.e., ambiguity function). For example, the Golay sequence, a type of complementary sequence used as pilot signals in the IEEE 802.11 WiFi system, has excellent autocorrelation property and is ideal for range detection in the static state. While in terms of Doppler/velocity detection, it exhibits a wide main lobe and high side lobes as shown in Fig. 6, which indicates low resolution for Doppler/velocity detection. Also, this technique requires continuous waveform along the fast time axis, which may not always be satisfied in a communication system, e.g., in an OFDM system where physical layer reference signals are used to perform sensing. In these cases, more advanced superresolution techniques can be considered to improve the sensing performance, which will be discussed in the remaining part of this section.

Sensing Parameter Estimation: There are several widely used parametric estimation algorithms to estimate sensing parameters: CLEAN, space-alternating generalized expectation maximization (SAGE), RiMax, MUSIC, and ESPRIT [84]. CLEAN is a computational algorithm that assumes the signal consists of multiple components and decomposes the signal into these components iteratively. After estimating the parameters relative to the strongest signal component, the processed signal is removed from the signal space. The processing repeats until a stop criterion is met. The CLEAN algorithm can not only be used to carry out interference cancelation but also to detect weaker targets [76]. When the number of parameters to be estimated is high, an exhaustive search is almost impossible. To address this issue, the alternating-projections method can be used [85]. In particular, the SAGE is an expectation–maximization (EM) algorithm that computes a maximum-likelihood estimation (MLE). It typically uses CLEAN algorithm's output as an initial guess and alternatively executes and iterates between E

and M steps until the whole process converges. SAGE refines the CLEAN estimation and removes all the unwanted signals during the parameter(s) estimation steps, but at a higher computational cost. Joint MLE (RiMax), another MLE algorithm, separates dense and specular components parameters into two separately sets, and estimates the parameters between these two sets alternatively to maximize the log-likelihood function [85]. RiMax outperforms CLEAN and SAGE in the dense multipath environment but with the cost of computation complexity.

MUSIC and ESPRIT belong to the subspace methods, that is, the noisy signal is separated into signal subspace and noise subspace, and both leverage the spatial covariance matrix to estimate signal parameters, such as Angle of Arrival (AoA), delay, and Doppler shift [19], [38]. MUSIC searches over the spatial directions to find the ones that are orthogonal to the noise space. Compared with MUSIC, Unitary ESPRIT has lower computation complexity as it computes the eigen vectors directly to estimate the angle, but it requires that the antenna array can be separated into two identical subarrays with known displacement between them. In general, MUSIC and ESPRIT provide less accuracy than SAGE in terms of parameter estimation, but with less computation complexity. Thus, they have been widely used in the literature for target detection. For instance, ESPRIT has been applied for multitarget detection and range-Doppler estimation in an IEEE 802.11p system assuming the perfect channel estimation [19], and MUSIC was used in [38] and [50] to estimate the velocity of the target.

Compressed Sensing: Compressed sensing, also known as compressive sensing, is a signal sparsity-based technique, which can also be used to estimate target parameters. This sparsity-based sensing technique is useful when the target scene is sparse and only a relatively small number of parameters need to be estimated, such as delay, Doppler shift, AoA, Angle of Departure (AoD), and the amplitude of signal echoes from the target. When the target scene can be presented with suitable sparse representation, the measurements can be taken below the Nyquist sampling rate and the target scene can be reconstructed reliably with sparsity sensing algorithms, such as basis pursuit, convex optimization, and Bayesian approach, among others [86]–[88].

Compressed sensing has been widely adopted in mmWave communications to estimate the mmWave channel through sparse signal recovery [89]. It has also drawn significant interest in radar sensing, aiming to achieve superior resolution and better accuracy. Compressed sensing has been reported outperforming the subspace method such as MUSIC algorithm in the noisy condition when strong dominant clutter and direct signal present [90]. Furthermore, since compressed sensing can reconstruct the signal with a small number of samples through optimization by exploiting its sparsity, it can cope with the situation that the continuous target observation may not be available, and the sampling interval may not be constant. Since ISAC systems often sense with limited radio resources, it may lead to fragmented channel measurements, spreading over time, frequency, and space. Additionally, data flows in ISAC systems in an on-demand fashion, making channel measurements taken at an irregular intervals. While traditional signal processing algorithms, such as MUSIC and ESPRIT, require continuous signal observation [91], compressed sensing can be a powerful tool to address these challenges in the ISAC system. Additionally, with compressed sensing, the number of pilot signals required to perform sensing can be significantly reduced, and the overall ISAC performance [92] can be improved.

Compressed sensing supports both on-grid sensing and off-grid sensing. The on-grid sensing discretizes the channel parameters to a set of grid values. In contrast, off-grid sensing can estimate continuous-value sensing parameters but at the expense of significantly high computational complexity and is challenging to operate in real time [91]. Compressed sensing can be used to estimate a single parameter at a time, as well as to support high-order estimation and estimate multiple multipath parameters simultaneously. High-order compressed sensing can improve estimation performance while adding more computation cost. There are some existing efforts to recover the channel using compressed sensing. For example, to aim at high-resolution channel reconstruction, Rahman *et al.* [79] leveraged the incoherent channel measurements in the received data block to formulate the parameter estimation problem as an on-grid sensing problem and employed the 1-D sensing technique to estimate channel parameters individually. Berger *et al.* [90] used the OFDM channel estimate results as the measurements and applied Basis Pursuit, a compressed sensing algorithm, to identify targets. With compressed sensing, high-resolution target detection can be achieved, but the processing complexity is much higher compared to traditional FFT processing. Zheng and Wang [93] used compressed sensing to perform joint delay and Doppler estimation on a passive OFDM radar system. The designed sensing algorithm takes into account the demodulation error of removing the modulated symbols, and performs off-grid parameter estimation through the atomic norm to account for the grid mismatch issue, that is, the sensing parameters may not fall exactly on the discrete grid points. Likewise, Maechler *et al.* [94] applied compressed sensing to target localization problems using the WiFi-based passive bi-static radar system.

E. Data Processing

The collected sensing data (i.e., RSS, CSI, or received waveform) will be preprocessed first to remove clutter and/or extract the target-related information such as range and Doppler frequency shift through the signal processing module. Furthermore, the extracted signal features will be processed by the data processing algorithms to support various sensing applications. Depending on sensing applications, data processing can be model-based, learning-based, or hybrid by combining model-based and learning-based approaches.

Learning Based: For human activity recognition and gesture recognition, in order to categorize detected human motion into one activity within a set of unique activities, learning-based classification algorithms are more commonly used. For example, Singh *et al.* [95] conducted human activity recognition measurements using mmWave radar. Based on the measurement data, this work compared several learning-based algorithms, such as support vector machines (SVMs) classifier, multilayer perceptron (MLP) classifier, bidirectional long-short term memory (LSTM) classifier, and time-distributed convolutional neural network (CNN). Among these classifiers, the combination of CNN and LSTM demonstrated the best recognition performance due to this method can explore the spatial and time dependency of the data. Zhao *et al.* [96] used mmWave radar operating at 77–81-GHz band for smart space applications, such as gait recognition and human tracking and identification. In their study, a deep recurrent network was used to perform the tasks. Differently, Lien *et al.* [83] used random forest classifier for gesture sensing using mmWave radar. Li *et al.* [97] used a simple 2-D CNN for activity classification. Moreover, Zhao *et al.* [98] inferred 3-D human skeletons using CNN. Sengupta *et al.* [99] used forked-CNN on the point clouds, i.e., the target echos collected using mmWave radar, to estimate and track human skeleton. In addition, learning-based algorithms have been used for localization. For instance, Koike-Akino *et al.* [100] measured the spatial beam SNRs using the IEEE 802.11ad/ay systems and leveraged a ResNet-based deep learning scheme for indoor localization.

Model Based: Model-based algorithms are often used to estimate sensing parameters and locate targets. For example, Nguyen and Heath [19] used ESPRIT for multitarget detection and range-Doppler estimation for automotive radar. Similarly, Li *et al.* [101] proposed a dynamic-MUSIC method to detect the reflected signal from the human body to localize the human target. The proposed method leveraged coherent receive signal can achieve a localization accuracy better than 0.6 m when the human target moves. Another example of the MUSIC algorithm is [50] using CSI information to extract Doppler velocity information via Doppler-MUSIC and using Doppler and AoA information to estimate human trajectories. With model-based approaches, the required amount of data can be reduced compared to machine learning, especially deep-learning methods. There are also some model-based approaches designed for gesture activities. For example, WiSee [15] used a Doppler-based gesture pattern matching approach to identify and classify a set of gestures.

Hybrid: Hybrid approaches combine the model-based and the learning-based algorithms to perform sensing. For example, Huang *et al.* [82] focused on fast indoor people detection and tracking. It uses the recursive Kalman filtering for tracking combined with the global nearest neighbor algorithm to associate tracks with people. Also, Wei and Zhang [102] combined the phase tracking algorithm and a decision tree to recognize touch-based gestures, allowing passive writing objects (such as pens) to be recognized with subcentimeter accuracy. Some hybrid methods also incorporate deep learning algorithms together with model-based algorithms. On this topic, Pegoraro and Rossi [103] used an extended Kalman filter to estimate the position and shape of the object, and further used a deep learning classifier to identify the subject. Zhao *et al.* [96] conducted human tracking and identification based on point cloud collected using mmWave radar. The proposed approach first uses the DBScan algorithm to cluster the objects and the Hungarian algorithm to associate the objects between frames. In addition, the Kalman filter was used to track and predict undetected objects in some frames, and finally, deep recurrent neural networks were adopted for gait recognition.

Recall that we have surveyed sensing and communication performance metrics used in the transmit waveform design. To evaluate sensing algorithms and systems, additional system-level performance metrics are needed. Moreover, depending on the use case, some metrics might be preferred. For example, cardinality measures (e.g., the number of valid motion trajectories or tracks, the number of false targets, and the number of missed targets) can be defined to measure the number of tracks associated with the truth and the number of missed and false tracks. These metrics are useful when the application requires counting and tracking multiple targets. An observation of cardinal measure over time can be quantified with detection probabilities and false positives. A finer metric to quantify the performance of a sensing system is sensing accuracy, which is defined as the difference between the sensed and true values of range, angle, velocity, or any other estimated parameter. Finally, latency (i.e., the time elapsed between an event and the availability of the sensing information) is an important parameter for time-sensitive sensing applications, such as industrial IoT and autonomous driving.

III. Applications

In this section, we introduce some typical applications for ISAC systems, including human activities, target localization and tracking, and others. In addition, we highlight how the sensing techniques enable these applications.

A. Human Activities

Liu *et al.* [24] provided a review of wireless sensing on human activities. Some representative human activities include gesture recognition, human identification, vital sign detection, and walking profiling. Human activity sensing can be integrated with smart home/building applications to monitor room occupancy, identify and locate people, monitor human well-being, support surveillance applications (i.e., safety protection and intrusion detection), and enable human interactions with smart computing systems and IoT devices. As an example, Li *et al.* [68] designed a passive WiFi radar system for human sensing, including breath detection and human counting, and addressed the issue that WiFi access points (APs) do not always have data to transmit. In their study, a beacon-only signal transmission scenario is evaluated, and an enhanced cross-ambiguity function (CAF) algorithm is designed to improve the Doppler performance. The key idea of the algorithm tends to synchronize and extract the beacon signal before passing through the CAF.

Human Counting and Identification: Xi *et al.* [72] addressed the issue of accurately estimating the number of human beings in a designated area and proposed a CSI-based scheme. After analyzing the correlation between the change of CSI and the number of people in the target area, this study adopts a metric called the percentage of nonzero elements in the dilated CSI matrix, which is highly correlated to the number of human beings. Wang *et al.* [30] proposed a system that uses commercial WiFi devices to recognize human targets based on the notion that the variation patterns on WiFi CSI are highly correlated to different people. Then, to characterize the pattern of human actions (such as walking), spectrograms from CSI measurements are generated, and corresponding features are extracted. In this work, the experiments are conducted on the measurement data collected in a room with 50 human beings, and the simulation results demonstrate that the system achieves the recognition accuracy of 80%–90%.

Human Activity Detection: Wang *et al.* [32] used CSI to detect and monitor human activities. The authors quantified the correlation of the CSI variation with the moving speed and used the movement speed of each human body part to detect human activity. The experiment setup consists of a laptop and an AP running IEEE 802.11ac protocol, operating in the 5-GHz frequency band with 20 MHz of bandwidth. The experiments demonstrated that 98% true positive rate can be achieved for small movements (i.e., pushing hand) and large movements (i.e., walking) when the target is at a distance up to 5 and 12 m, respectively.

Indoor Human Localization and Tracking: Intrusion detection and human tracking are important to enable smart home applications. For indoor human tracking, Li *et al.* [50] used the CSI information to extract Doppler frequency. This work addresses random CSI phase offset in each CSI measurement and designs a mechanism to adjust the power level of each antenna so that the desired Doppler component can be obtained. In this study, MUSIC-based Doppler estimation is applied, and estimated Doppler and AoA spectrum are adopted jointly to estimate the human trajectory. Also, Li *et al.* [101] presented a WiFi-based device-free passive indoor localization system, where a dynamic-MnIC algorithm is designed to detect and identify the human target angles. Using the off-the-shelf NIC, the proposed algorithm demonstrates a median location accuracy of 0.6 m for walking human targets.

Gesture Recognition: WiFi signal has been used to carry out hand gesture recognition [36], [104], [105]. For instance, IEEE 802.11bf, an ongoing WiFi sensing standard, is defining some gesture recognition use cases [106] as follows: the short-range ($<$ 0.5 m) gesture recognition should deal with the identification of a gesture from the movement of finger(s); the medium-range ($>$ 0.5 m) gesture recognition should deal with the identification of a gesture from the movement of a hand; and the large-range ($>$ 2 m) gesture recognition: which deals with the identification of a gesture from full-body movement.

One challenge of human gesture recognition is that it is highly sensitive to position and orientation (for example, facing the transmitter or not). To address this issue, Virmani and Shahzad [105] proposed a translation function; with the designed function, only one configuration of all gestures is required, and virtual samples for all configurations can be generated based on the designed translation function. When the model is in use, the user's configuration will be first automatically estimated, and then the gesture will be evaluated against the classification model for the estimated configuration. The authors also demonstrated that the translation function could improve gesture recognition accuracy.

High-frequency bands, such as mmWave and Terahertz, can be used to refine the granularity of gesture recognition, thanks to large bandwidth and enhanced spatial resolution brought by narrow beamwidth. For example, Wang *et al.* [107] investigated the use of Terahertz radar to conduct microgesture recognition. In their study, the changed motion between gestures is characterized based on a range-Doppler map and a CNN-based deep learning technique is used to recognize different gestures. Likewise, Wang *et al.* [108] investigated Terahertz radar to carry out fine-grained gesture recognition. In their work, the range profile sequence as the key feature is extracted from the radar signal and the random forest-based machine learning scheme is used to establish the model from the extracted features. To improve efficiency, the principal component analysis (PCA)-based dimensionality reduction is also utilized.

Vital Sign Monitoring: Adib *et al.* [17] used wireless signals to monitor human breathing and heart rate. The minute movement of the chest and the skin due to breathing and heart beat can be detected from the reflected wireless signal by measuring the phase variations. The authors demonstrated that the monitoring device could track a person's breathing and heart rate even in different rooms. Furthermore, the device can also monitor and track multiple people's breathing and heart rates simultaneously. In this study, the authors also built a real-time FMCW radio prototype to develop several insights. As another example, Liu *et al.* [109] considered commercial WiFi devices to track breathing and heart rate during sleep by utilizing channel knowledge, demonstrating that the system can work well with two people laying on a bed.

Writing Recognition/Computer Human Interaction: Cao *et al.* [35] addressed the writing recognition issue and designed a WiFi signal-based system. The designed system leverages the CSI values from WiFi devices to detect the motion of hands and fingers, leading to the recognition of corresponding written letters.

It is worth noting that mmWave WiFi sensing has received increasing attention recently and has brought new sensing opportunities. Millimeter-wave communications employ highly directional and electronically steerable antennas to achieve their required communication range. Due to its high angular resolution, the narrow beam can better track small and fine-grained motion. Thanks to their smaller size and widespread availability, mmWave devices can be easily deployed to support various IoT applications, such as human sensing and area mapping. Aside from these benefits, mmWave WiFi sensing has its own challenges. For example, due to the directional antenna and limited antenna FOV, multiple beams are often required to cover an area; therefore, beam pattern design, beam training, and beam tracking are essential in mmWave WiFi communication and sensing. In addition, the low-cost mmWave WiFi devices, such as the IEEE 802.11ad/ay systems, have limited antenna elements and may not be able to produce high-resolution angle estimation by default. To address this issue, superresolution angle estimation algorithms are often required. Related to this direction, Wei *et al.* [110] designed E-Mi, a framework to use 60-GHz radio channel to reconstruct the environment and reflectivity to predict communication signal strength for a given deployment.

B. Localization and Tracking

In addition to human beings, other objects such as vehicles can be localized and tracked via ISAC.

Automotive Radar: Autonomous driving vehicles need to constantly monitor the environment, assessing the distance and velocity of surrounding vehicles to avoid a collision or participate in vehicle platooning. On the other hand, communication is important for autonomous vehicles to stay connected and exchange information; thus, leveraging the communication waveform for vehicular sensing has drawn significant interest recently.

Some research efforts have been focusing on using communication waveform for automotive radar. For example, an IEEE 802.11ad-based automotive radar [63] is proposed using SC PHY. The preambles, consisting of Golay complementary sequences, are used for target detection, as well as range and velocity estimation for single target and multiple targets scenarios. Through a simulation study, the feasibility of simultaneous centimeter (cm)-level range detection accuracy and cm per second (cm/s)-level velocity accuracy, as well as a gigabits-per-second data rate, are demonstrated. In addition to SC PHY, Control PHY of IEEE 802.11ad is also explored to support automotive radar applications. In particular, sector-level sweeping is exploited to perform target detection and range/velocity estimation [46]. In addition to IEEE 802.11ad, IEEE 802.11p, which is an OFDM-based waveform, is studied for vehicle range and velocity estimation through simulation [19].

Moreover, some experiments using a prototype have been conducted to perform automotive radar functions [18]. The prototype consists of directional antennas and software radio transceivers to transmit the IEEE 802.11a/g waveform to estimate ranges in a vehicular environment.

C. Other Applications

Area Map Reconstruction: Taha *et al.* [111] constructed an augmented reality (AR) and virtual reality (VR) depth map for mixed-reality experience using IEEE 802.11ad SC PHY. More specifically, a beamforming codebook is designed to steer the overlapped beam to a rectangle grid in the xz plane to obtain the backscatters from objects for sensing. Furthermore, successive interference cancelation and joint beam processing are performed to construct the depth map. For performance evaluation, a detailed multipath propagation model is generated using the commercial ray-tracing tool.

Smart City: As an important IoT/CPS application, smart cities tend to optimize city operation so that energy efficiency, transportation services, people's health and wellness, and economy can be improved by leveraging the information and communication technologies [112]. In smart city applications, RF signals can be used to monitor traffic or control street lights. For example, WiTraffic [20], a WiFi-based traffic monitoring system implemented using off-the-shelf WiFi devices, analyzed the CSI pattern of the reflected signal from the passing vehicles and conducted vehicle classification, lane detection, and speed estimation. Experiments were performed on both highways and local roads, showing around 96% accuracy of vehicle classification and lane detection.

Besides the traffic monitoring, the RF sensing data collected by wireless devices through mobile crowdsensing (MCS) [113] can be used to estimate human occupancy in a tourism site or an indoor restaurant, which can provide real-time information to customers. Furthermore, the collected human activity data can be shared and compared within community to promote healthy living style. Compared with traditional sensors in sensor networks, these wireless devices have better communication, sensing and data processing capabilities [113].

In-Cabin Monitoring: In-cabin monitoring can support a number of safety features, including driver behavior monitoring, reckless driving recognition, authorized driver identification, passenger health monitoring, passenger counting, and child presence detection to avoid leaving a child behind in an unattended vehicle, among others [114]. For example, WiFind [115] detected driver's fatigue by leveraging the self-adaptive method to recognize the body features of the driver in multiple modes using WiFi signal. The experiments conducted in the real-time driving environment demonstrated the detection accuracy of 89.6% can be achieved with a single driver. Likewise, WiDrive [116] designed a WiFi-based driver activity recognition system to prepare safe driver takeover in the autonomous vehicle. It realizes the real-time recognition of driver's activities through a hidden Markov model (HHM).

Environment Monitoring: Large-scale wireless networks (such as cellular networks) can assist environmental studies. Rainfall measurement, pollution monitoring, fog, snow, and sleet detection are potential applications that can be enabled by analyzing the changes of the wireless propagation due to atmospheric phenomena. Related to this direction, Messer *et al.* [21] demonstrated the feasibility of measuring the RSS level in the cellular backhaul links to monitor surface rainfall level with reliable performance.

IV. TOOLS AND DATA SETS

In this section, we introduce some tools[1] and publicly available data sets that can be beneficial to carry out ISAC research in practice.

A. Tools

Linux 802.11n CSI Tool [70]: It is a widely used WiFi CSI collection tool running on a commodity IEEE 802.11n NIC. This tool measures each packet preamble at the receiver for every transmitter and receiver pair. The toolkit works with the Intel WiFi link 5300 wireless NIC and reports CSI for 30 subcarriers, which are evenly spread in the entire bandwidth [70].

[1]Certain commercial equipment, instruments, or materials are identified in this article in order to specify the experimental procedure adequately. Such identification is not intended to imply recommendation or endorsement by the National Institute of Standards and Technology, nor is it intended to imply that the materials or equipment identified are necessarily the best available for the purpose.

Talon Tools: Talon Tools [117] is a software toolset working with TP-Link's Talon AD7200 router, supporting IEEE 802.11ad. The Talon router consists of a phased array antenna with 32 antenna elements, which can be individually controlled to change the magnitude and the phase. With the toolset, the Talon router can be used to study 60-GHz mmWave communication in realistic environments. The tools included in the toolkit are LEDE, Talon AD7200 Sector Patterns, and Nexmon, which is a C-based patching framework that can be used to develop the customized firmware patches to complete certain tasks, such as accessing the RSS of sector sweep frames and extracting the CSI of OFDM-modulated WiFi frames (802.11a/g/n/ac) for each frame with up to 80-MHz bandwidth [71]. LEDE provides an interface to configure the router to set up communication links between multiple devices. Talon AD7200 Sector Patterns are a tool that can be used to measure the beam and sector patterns.

TI mmWave Radar Sensor [118]: TI mmWave radar operates in the mmWave frequency range with 4-GHz bandwidth. It includes transmitter, receiver, and signal processing modules and employs radar waveform such as FMCW for sensing. The output of the sensor is the point cloud, including a set of reflection paths with range, angle, and radial velocity information.

SimHumalator [119]: This tool targets human radar signature models in passive WiFi radar scenarios [120]. It leverages IEEE 802.11 WiFi compliant waveforms (i.e., 802.11g, 802.11n and 802.11ad) for sensing and outputs micro-Doppler features of human targets.

WiGig Tools [121]: WiGig Tool is a set of open-source tools to simulate IEEE 802.11ad/ay WLAN systems, which can facilitate mmWave sensing research with the standardized communication waveform. The tool package consists of the following tools.

1) *NIST Q-D channel realization software* leverages full 3-D ray tracing to model the specular reflections between two reference points in space, and the diffused paths are reconstructed based on a statistical model obtained from NIST measurements [122]. The modeled propagation paths are described by their magnitude, phase, time of arrival, AOD, and AOA. Furthermore, by raytracing the close-located antenna elements in space, the software is capable of supporting the spatial correlation between different MIMO streams. Recently, the software has been enhanced to support the ray tracing of targets, as explained in Section II-B.
2) *NIST IEEE 802.11ay PHY* is a digital transceiver model that supports the main features of the IEEE 802.11ay PHY [8], [123]. It supports SU-MIMO and MU-MIMO for both OFDM and SC modes. The implemented digital transceiver can perform channel synchronization and channel estimation using the preamble provided in the IEEE 802.11ay packet, which can be further utilized for sensing applications.
3) *NIST Q-D Interpreter Software* is a visualization tool that can visualize the environment along with targets and also analyze the ray tracing and PHY simulation results.

B. Data Sets

Table I lists a set of publicly available data sets. In the table, we provide the information of 12 data sets, which consider different sensing applications. For each data set, we provide the data set name, the application that can be applied, the organization that provides the data set, the note that includes some key properties of the data set, as well as the Web link to directly access the data set. From the table, we can see that some data sets are CSI measurements for WiFi signals, such as IEEE 802.11n and 802.11ad. Several data sets are collected from mmWave radar sensors applied for indoor sensing.

V. STANDARDIZATION

As ISAC can provide numerous benefits and support a variety of emergent applications, it has received growing attention from not only the research community, but also the standardization organizations. In particular, IEEE has recently initiated an effort toward IEEE 802.11bf WiFi or WLAN sensing, the specification that will turn WiFi devices into object sensors to perform enhanced sensing operations in frequency bands between 1 and 7.125 GHz and above 45 GHz.

Different from the broader WiFi sensing research efforts, which focus on building sensing prototypes and designing algorithms to provide better sensing solutions, the objective of the IEEE 802.11bf standards development tends to address interoperability challenges by defining sensing procedures and protocols to allow the sensing devices to effectively work in a system. In particular, a WLAN sensing procedure is being proposed to allow discovering available devices for sensing, forming sensing groups, defining required sensing measurements, and feeding back sensing results. The suggested WLAN sensing procedure is composed of one or more of the following: sensing session setup, sensing measurement setup, sensing measurement instance, sensing measurement setup termination, and sensing session termination [136]. It is worth noting that the directional multigigabit (DMG) sensing procedure is a subset of the WLAN sensing procedure, specifically targeting the frequency band above 45 GHz. The DMG sensing procedure consists of an extra DMG sensing burst session than WLAN sensing, allowing DMG sensing burst to expand over multiple DMG sensing instances to obtain more accurate Doppler shift estimation.

Several roles have been defined for the devices participating in the sensing procedure [137]: 1) sensing initiator is a station (STA) that initiates a WLAN sensing procedure and requests the sensing results; 2) sensing responder is a non-initiator STA that participates in a WLAN sensing procedure initiated by a sensing initiator; 3) sensing transmitter is an STA that transmits packets used for sensing measurements in a sensing procedure; 4) sensing receiver is an STA that receives packets sent by a sensing transmitter and performs sensing measurements in a sensing procedure; and 5) sensing processor [138] is an STA that processes the sensing measurements (e.g., raw CSI and received waveform) and obtains the sensing result after signal processing (e.g., compressed CSI,[2]

[2]In compressed CSI, the measurement vector that need to be feedback has reduced dimensions in comparison to the full CSI [139].

TABLE I
AVAILABLE SENSING DATA SETS

Dataset Name	Application	Provider	Notes
CSI for six activities [123]	Human activity recognition	University of Twente	This dataset consists of CSI collected for 6 activities by 9 unique participants over a total of 6 days with IEEE 802.11n. Sampling frequency is 50 Hz.
SignFi [124]	Sign language recognition	William & Mary	This dataset contains CSI traces collected from 5 users. The data was collected in a lab environment for users 1-4, while for user 5, data was collected in both lab and home environments using IEEE 802.11n based CSI tool. A total of 276 sign words were performed in this dataset.
Indoor WiFi human activity recognition dataset [125]	WiFi-based human activity recognition	Jordan University of Science and Technology	This dataset was collected using the Intel 5300 NIC for WiFi-based human activity recognition in LoS and non-LoS indoor environments.
mmBSF [126], [127], [128]	Indoor localization	MITSUBISHI Electric Research Laboratories	This dataset consists of beam SNRs collected using IEEE 802.11ad commercial routers.
mmWave gesture dataset [129]	In-air gesture recognition	Beijing University of Posts and Telecommunications	This dataset comprises 56 420 gesture sample instances from 144 volunteers, 1357 minutes of data in total, collected using mmWave Radar.
RadHAR [96]	Human activity recognition	University of California Los Angeles	This dataset consists of five human activity data in the format of point clouds collected using mmWave radar. The five activities include boxing, jack, jump, squats, and walk.
Radar signatures of human activities [130]	Human activity monitoring and fall detection	University of Glasgow	The data was collected using an off-the-shelf FMCW radar operating at 5.8 GHz band with 400 MHz bandwidth and 1 ms chirp duration.
mmWave Radar Walking Dataset [131]	Human gait recognition	Università Politecnica delle Marche	This dataset recorded 6 activities such as slow walking, fast walking, slow walking with hands in pockets.
Human gait in "mmWave" eyes [132]	mmWave gait recognition	Beijing University of Posts and Telecommunications	The data set contains two types of walking trajectories, i.e., fixed-route and free-route. A total of 30 hours of 3D point cloud data were collected with 95 volunteers, and up to 5 people walking at the same time.
mBeats [133]	Heart rate sensing	University of Oxford	This dataset contains 180 minutes of data collected from two subjects in the sitting and lying positions using mmWave Radar.
DeepSense 6G [134]	Beam prediction, position, and object detection/ classification/tracking	Arizona State University	This dataset consists of coexisting multi-modal sensing and communication data collected in realistic wireless environments. The multi-model data includes data collected from wireless communication, camera, GPS devices, LiDAR, and Radar.
WALDO [135]	Indoor human localization	National Institute of Standards and Technology (NIST)	Data was obtained through simulation using IEEE 802.11ay PHY software. The dataset was generated using a multi-static radar configuration, with each device consisting of multi-antenna elements. There are multiple people in the scene, each with their own unique movement dynamics.

range-Doppler map, and range-time map). Note that the sensing processor needs to process the measurements and further feedback sensing results to the sensing initiator in case the sensing initiator and the processor are different STA. In the sensing procedure, the sensing initiator and sensing responder can be either a sensing transmitter, sensing receiver, or both, and sensing can be performed using either uplink or downlink transmissions.

It is also worth noting that sensing measurement and reporting is one of the important issues especially for the case when sensing receiver that performs the measurements is not a sensing processor. To reduce the size as well as the number of feedback for reporting the measurements, the following approaches have been proposed.

A. Truncated Channel Impulse Response-Based Sensing Measurement and Reporting

In truncated power delay profile (PDP) or channel impulse response (CIR)-based sensing measurement and reporting, the following steps can be considered. In the first step, the CFR, i.e., CSI in frequency domain is converted to CIR (time domain) using inverse discrete Fourier transform (IDFT) such as inverse FFT (IFFT). Subsequently, in the second step, only the subset of complex samples corresponding to the range of interest of the entire CIR [140] is reported to the sensing initiator or processor. This scheme can significantly reduce feedback overhead and can also provide complete/full information within the range of interest with lower side-lobe level in comparison to grouped CSI (frequency domain) where IFFT is performed on a subset of the total subcarriers.

B. Threshold-Based Sensing Measurement and Reporting

As mentioned earlier, a sensing initiator can act as a transmitter, receiver, or both or neither whereas a sensing responder can act as a transmitter, receiver, or both. Note that if a sensing initiator is a sensing receiver, there is no feedback needed since the sensing initiator can directly obtain the measurements to get the sensing result. On the other hand, if a sensing initiator is a sensing transmitter, feedback is required to get CSI measurement (e.g., compressed CSI and sensing result) from sensing receiver(s). Threshold-based sensing measurement and reporting procedure has been specified in [137] as an optional procedure applied to trigger-based sensing.

The frequency of feedback depends on the use cases. Some use cases, such as intruder detection, require frequent CSI feedback, but most of the feedback may be highly correlated over a period. Thus, the sensing receiver does not need to feedback the CSI all the time. The receiver can feed back only when the CSI variation becomes large. For this purpose, a threshold can be used in the reporting phase of the procedure. This procedure is known as the *threshold-based sensing measurement procedure* [137], [141]. If the CSI variation meets the feedback threshold criteria, i.e., if the CSI variation is greater than the threshold, the sensing receivers will send the feedback response to indicate that they will perform further feedback, and then the feedback will be triggered by the sensing transmitter and finally sensing receiver can feedback the received null data packet (NDP), CSI, compressed CSI, or the final result.

The CSI variation could be quantified by the time-reversal resonating strength (TRRS) [142], which is the maximal amplitude of the entries of the cross-correlation between two complex CIRs. This scheme is more robust than conventional correlation coefficients since it takes the maximum value of the correlation coefficients [142]. However, one can also propose a better metric to evaluate CSI variation. Thus, the calculation of CSI variation is suggested to be implementation specific, where different devices can have different methods to determine CSI variation. However, the estimated value of CSI variation needs to be mapped to a closed interval [0,1] to quantify the degree of variation, where 0 and 1 indicate the minimum and maximum CSI variation, respectively.

As an example, we consider an empty indoor environment with two moving targets and two mmWave communicating devices each consisting of a single antenna, as shown in Fig. 7(a). The normalized CSI variation for this scenario assuming perfect channel knowledge can be seen in Fig. 7(b), where the TRRS scheme is used. One can observe that for each time when CSI variation is below the threhsold, the CSI measurement feedback is not required. Thus, different values of threshold in feedback threshold criteria result in the different number of feedback required to report the CSI measurements. As shown in Fig. 7(c), if we increase the threshold value from 0 to 0.04, the number of feedback reduces by 30 %. This feedback can be further reduced to 50 % by increasing the threshold to 0.06. Nonetheless, the velocity versus time plot does not degrade significantly even though the feedback is reduced by half. In Fig. 8, we can clearly identify the movement of two targets through two stronger oscillations in all three cases. Note that Fig. 8(a) corresponds to the ground truth utilizing all the CSI measurements by considering threshold value equal to 0. On the other hand, Fig. 8(b) and (c) corresponds to the cases utilizing 30% and 50% CSI measurements, respectively, by setting threshold value as 0.04 and 0.06.

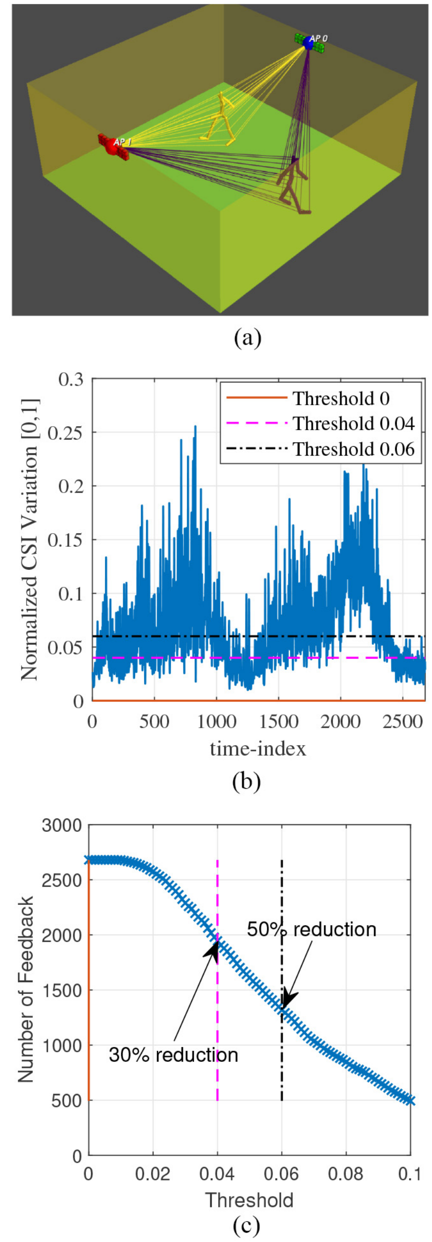

Fig. 7. Threshold-based WLAN sensing measurement and reporting under perfect channel knowledge, where threshold = 0 means that CSI measurements always need to be feedback even though the channel does not change for the entire duration. (a) Living room environment with two targets. (b) Normalized CSI variation over time. (c) Impact of threshold on the number of feedback.

VI. Challenges and Future Research Directions

In this section, we present challenges and some important research directions.

A. Challenges

By using the communication waveforms for sensing and leveraging pervasive wireless networks, sensing services are very promising to become an integral part of the next-generation wireless system. However, there are a number of challenges that need to be addressed.

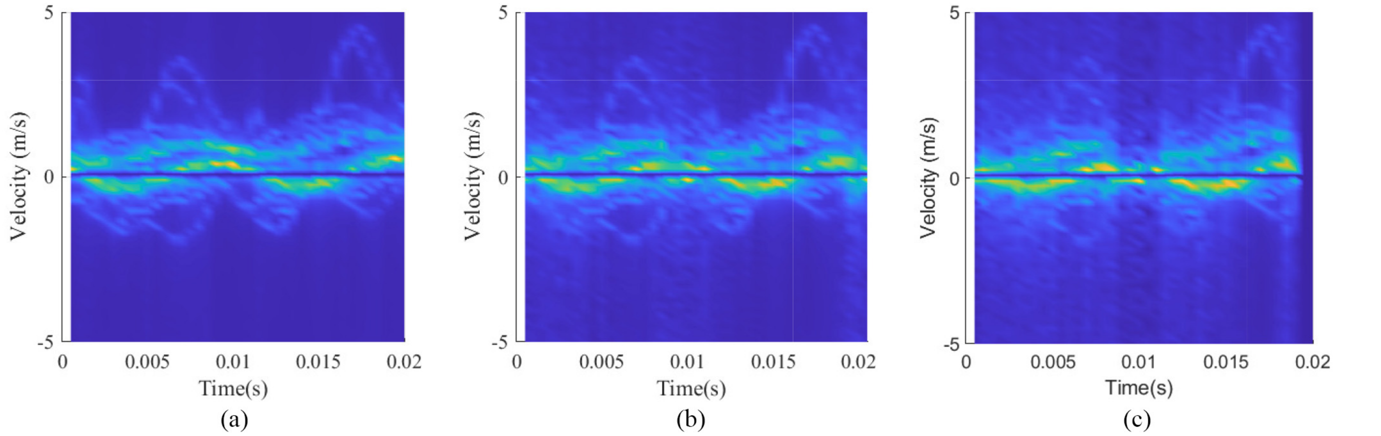

Fig. 8. Velocity versus time considering threshold-based WLAN sensing measurement and reporting with different values of threshold. (a) Threshold = 0. (b) Threshold = 0.04. (c) Threshold = 0.06.

First, to support an application, in the existing research, sensing is commonly conducted in one particular environment with a fixed geometric setting, and the sensing performance can be significantly affected by numerous factors such as relative distance between the target and transmitters/receivers, the number of targets in the area, and the RF waveforms used for sensing, among others. In addition, mutual impact and assistance between sensing and communication have not been thoroughly studied. Thus, it is important to leverage collaborative sensing, communication-assisted sensing, and sensing-assisted communication to optimize the system, achieve good integration gain, and use SDN and distributed edge computing to build a sensing ecosystem to achieve ubiquitous and reliable sensing.

Second, applications for an ISAC system are diverse, and applications have various performance requirements in terms of sensing accuracy and communication QoS. To compare different systems and algorithms within the ISAC context, dedicated performance indicators inherited from both communication and sensing technologies need to be considered. In wireless communication, the goal is to ensure a seamless user experience independently of environmental factors. Thus, peak data rate, average data rate, and latency need to be respected under different connection density (devices/km^2), mobility (km/h), and area traffic capacity (Mbit/s/m^2). Whereas, for RF sensing, the goal is to detect, locate, or track one or multiple targets with high accuracy independently of environmental factors. For example, in an industrial IoT environment, where a robot needs to perform high reliable and high precision tasks, subcentimeter level accuracy with *ms* one-way latency and reliability of up to 99.9999% may be required [3], [143]. To support such ultralow latency, highly reliable, and precise industrial applications raises a challenge for ISAC design. Given limited resources, designing a cost-effective ISAC to satisfy performance requirements from both communication and sensing functionalities raises new challenges to system design and integration. To this end, some important research areas include improving performance by carrying out cross-layer and cross-component design, the investigation of high-fidelity channel model and target model to assist system design, and others.

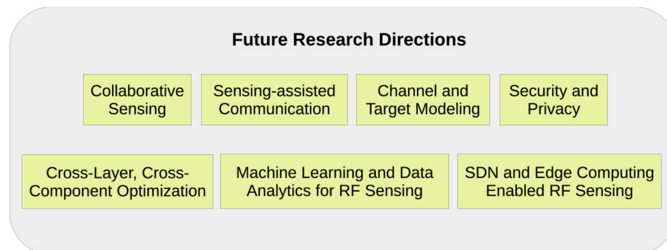

Fig. 9. Future research directions for ISAC.

Third, the ISAC system can generate massive amounts of data to be processed in a timely manner. Also, the system could operate in a dynamic environment with numerous uncertainties. On the one hand, to make the collected data useful to support applications, it is challenging to effectively extract valuable knowledge from massive amounts of sensing data rapidly. On the other hand, the collected sensing data could contain privacy-sensitive information, and balancing the privacy and utility of the data is an unsolved issue. In addition, the ISAC system could be subject to component failures, security threats, etc. For instance, in an ISAC system, to accomplish sensing, a transmit signal with a significant power level will illuminate the target. The illuminating signal may contain messages for the intended communication receiver, which can be disclosed to adversaries and subject to a variety of attacks. Thus, it is important to systematically investigate the security risk of ISAC systems and develop corresponding countermeasures to make ISAC secure. To this end, new research areas should include the foundation and application of machine learning and big data analytics for radar sensing, security, and privacy in ISAC systems and others.

B. Future Research Directions

In the following, we introduce several critical areas of research, as illustrated in Fig. 9.

1) Collaborative Sensing: Currently, most RF sensing systems target one particular application and are highly dependent on the deployment of sensors and the environment. In order to better adapt the sensing systems to a real-life scenario

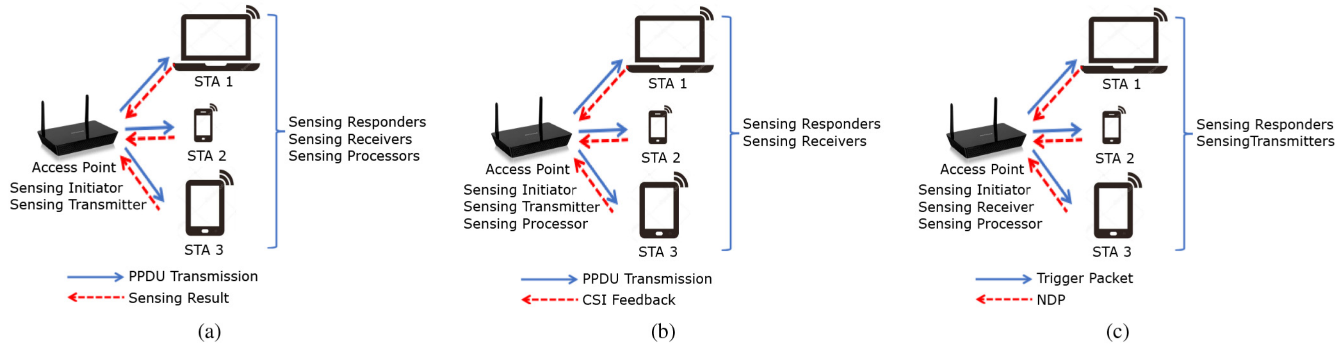

Fig. 10. Collaborative WLAN sensing with three possible implementations. (a) First implementation, (b) second implementation, and (c) third implementation.

and take advantage of the ubiquitous availability of wireless devices, collaborative sensing is an important enabling technology.

In collaborative sensing, multiple devices can collaborate as a group to capture additional information about the surrounding environment. Fig. 10 presents three possible ways of implementing collaborative sensing utilizing the roles considered in the IEEE 802.11bf amendment as described in Section V. In the first implementation, as shown in Fig. 10(a), multiple STAs can forward their sensing results directly to the initiator (i.e., the device initiated the sensing procedure) after processing the CSI measurements, and the AP initiator can combine each of the sensing results to make a final decision. In some use cases, for example presence detection, one-bit feedback from each STA to indicate the presence status can be considered. In the second implementation, as shown in Fig. 10(b), since the initiator acts as a processor, which directly processes the CSI measurements, multiple STAs can feedback their CSI measurements in an orderly fashion. In this way, AP can capture additional information about the surrounding environment since the raw measurements of multiple channels would be available. In the third implementation, as shown in Fig. 10(c), the initiator acts as a receiver and also as a processor. In the beginning, the initiator forwards a trigger packet to all STAs, and in response to the trigger packet, each responder transmits a CTS-to-self packet if it is available to participate in sensing (known as the polling phase). Subsequently, the initiator retransmits the trigger packet to all STAs that agreed to participate, and in response to the trigger packet, each STA transmits an NDP one by one to sound the channel.

In this area, the following issues should be addressed: 1) how to organize the collaborative sensing groups? If there are too many participants, too much redundant information will congest the communication network and degrade the communication performance; 2) related to protocol design, how to dynamically organize the sensing group for different sensing tasks? 3) how often should the sensing be performed with the consideration of application requirements and the number of participants involved in sensing tasks? 4) how much information should be processed locally, and what is the granularity of the sensing information that should be collected, aggregated, and processed by networking and computing infrastructure so that timely important knowledge can be provided to applications. Fine granularity may allow the use of more advanced data mining/fusion and machine learning techniques, but it incurs more overhead and longer processing time. Thus, it is interesting to determine the desired granularity level for supported applications, and applications may have different granularity levels to support; and 5) it is critical to have a fundamental understanding of sensing performance and its fundamental limitation.

2) Sensing-Assisted Communication: A significant amount of research work has been done on utilizing existing communication systems to perform sensing tasks. In the meantime, sensing should also assist communication, which is especially important and beneficial for communication in high-frequency bands, such as mmWave and Terahertz bands. Due to high propagation loss in these bands, beamforming and often narrow beams have been used to compensate for the path loss. When the receivers or transmitters are in motion, the communication links (i.e., the direction of beams) must be constantly reconfigured to keep good alignments and thus, maintain the desired throughput. Beam reconfiguration through training and beam refinement can be expensive, especially in the narrow beam (e.g., pencil beam) setup involving fast motion. In this case, if the location and trajectory of the receivers can be estimated, or changes in the surrounding environment can be predicted, the beam can be adjusted in time, significantly reducing the need for beam training or beam refinement. For example, in the vehicular network, the beam tracking overhead can be reduced by tracking and predicting the kinematic parameters of vehicles [144].

In addition, a real-time area map obtained through sensing can be used to predict blockage and pick up another propagation path to continue data transmission if the current communication link is going to be blocked. One challenge of designing ISAC systems is to perform simultaneous environment sensing, user localization, and trajectory tracking while maintaining high communication throughput. Other issues include how to translate the sensing results to communication design in real time. It is worth noting that with the increasing interest in 6G Terahertz communication, sensing is becoming an integral and necessary component to support communications. In this regard, some emergent techniques such as the reconfigurable intelligent surface (RIS) can be leveraged to extend communication range through intelligent beamforming, which heavily relies on real-time environment sensing to perform environment-aware beamforming [145]. Thus, the modeling, simulation, testbed, and standardization about leveraging sensing information to assist communication in the next-generation wireless systems shall be further researched.

3) SDN and Edge Computing-Enabled Wireless Sensing: RF sensing can be ubiquitous and cost effective. Collected wireless sensing data need to be integrated with data collected from other sensors [e.g., image sensors, laser imaging, detection, and ranging (LIDAR)] to help smart environments make accurate decisions. In a smart environment, some areas may be covered by existing sensors (e.g., surveillance systems in a building or a campus) and may capture a number of physical objects (humans, intruders, etc.). However, existing sensing infrastructure may not cover all areas and may not work in all conditions. When some objects (e.g., intruders) enter the noncovered area, it is critical to engage RF sensing. In order to achieve this, the state of the physical object needs to be tracked, and the RF sensing function should be dynamically turned on and off. To achieve seamless integration of heterogeneous sensor groups and dynamically enable tracking and sensing policies, SDN technology should be considered to provide a common interface to allow the system dynamically execute sensing policies within or across multiple sensing systems, greatly supporting the vision of the smart environment.

Also, a sensing ecosystem should consider distributed edge computing for sensing data processing. Edge computing, as a new distributed computing infrastructure, has shown great potential to support a number of smart-world IoT systems [146]. In a large-scale sensing system, transmitting massive amounts of data collected by sensing devices to the cloud will introduce significant overhead to the network, causing network congestion and long latency due to data transmission. To mitigate against this, distributed edge computing will be capable of providing sensing data processing near to devices or even on devices locally. The edge computing in ISAC systems shall consider the management of edge nodes and coordination of procession on RF sensors and edge nodes. Also, as transmitting sensing data to edge nodes may pose an overhead to wireless communications, how to efficiently manage the computing and network resources of RF sensors and edge nodes should be carefully studied.

4) Cross-Component and Cross-Layer Design and Optimization: Numerous smart-world IoT applications have strict performance requirements in terms of both sensing (e.g., accuracy, real time, and reliability) and communication (e.g., throughput, latency, and reliability) [3]. In an ISAC system, sensing and communication share time, frequency, spatial, and power resources. It is important to conduct resource management to satisfy performance requirements for both sensing and communication.

To meet performance requirements, cross-component design and optimization shall be considered. Sensing involves multiple components as shown in Fig. 1, including transmit waveform generation, sensing environment, signaling processing, and learning-based or model-based sensing algorithms. When studying a sensing solution, the impact of individual components should be carefully considered. For example, the sensing environment, such as the deployment of the transmitter and the receiver, target location, and sensing application requirements, should guide the transmit waveform design and configuration. In addition, appropriate signal processing techniques and sensing algorithms should be selected depending on the adopted waveform and accuracy and latency requirements.

Furthermore, the cross-layer design shall be considered. ISAC system can be mapped into a layer structure, including physical object layer, sensing and communication layer, and application layer. The physical object layer consists of different types of objects (e.g., humans and vehicles) as sensing targets, which can be either static or mobile. The sensing and communication layer engages the radar-based sensing and communication components to track the state of the physical objects of interest and provide communication services simultaneously. The application layer consists of a number of smart-world applications, including smart home, smart healthcare, smart city, and smart transportation, to name a few. Many such smart-world applications have stringent performance requirements in terms of sensing and communication. Thus, a critical problem is enabling radar sensing, collecting and aggregating data related to radar sensing, and storing and processing the data in real time to support application requirements. It involves cross-layer design, including sensing infrastructure, communication network, and computing-driven data process and analysis. Thus, it is essential to jointly design sensing, control, communication, and computing to optimize the overall system performance.

5) Channel and Target Modeling: Existing studies have focused on single or multiple sensing tasks involving several sensing transmitters and receivers. These studies have demonstrated the feasibility of sensing applications, but the performance can often be affected by system deployment and application requirements. In order to integrate these sensing entities to accomplish more complicated tasks in support of emergent smart-world IoT applications, we need to study a more large-scaled and more complicated system consisting of more entities to gain the fundamental understanding of the design issues and its expected baseline performance before actually deploying it. To support this effort, an accurate channel model and target model are essential.

To model the communication channel, the hybrid channel model (i.e., a combination of deterministic and statistical approaches) has been widely used, especially for evaluating mmWave communication systems. In particular, the channel MPC parameters (i.e., path gain, delay, 3-D AoA, AoD, and Doppler shift at each simulation instance) should be modeled to help design beamforming and evaluate communication performance. In ISAC, obtaining an accurate target model is paramount. In the wireless sensing environment, as the distance between the signal emitter and the target is relatively closer than in a traditional radar system, the target, in general, cannot be modeled as a simple point target but rather an extended target with multiple scattering centers, and intensity of rays from these scattering center can be modeled using RCS. There are some existing research efforts on using electromagnetic methods to compute the rays reflected or scattered off the target [58], [66], but these methods are too computationally intensive to generate rays in real time to support system-level simulation. A desired channel model should have a good balance between accuracy and complexity. The model should consider the various polarization configuration between transmitter and receiver antenna. In addition, it is critical to accurately model the time-varying property of channels, especially the target, to enable sensing.

Another essential issue is how to determine the proper scatter centers in order to model the target. It is critical to model the RCS value, which is dependent on the incident angle, reflection/scattering angle, the shape of the target, material, and waveform frequency. In addition, when the target is in motion, which may involve the local motion of target components or scattering centers, the relative scattering centers of the target may change, and each scattering center may have its own local moving speed and direction. Other issues include modeling the RCS value over time while maintaining phase continuity, determining the correlation time and distance for this channel, and designing a statistical model that considers the target speed, direction, and motion type.

6) Machine Learning and Data Analytics for RF Sensing: Machine learning, especially deep learning, has shown a great ability to transform data collected from disparate systems and generate insightful knowledge to make intelligent decisions and achieve automation. With the support of high-performance computing (edge/cloud computing) and advanced networking and communication technologies, machine learning has shown great success in a number of areas, including enabling the intelligence of IoT systems [147]. In order to apply machine learning and data analytics to radar sensing, it is critical to have a good understanding of the application performance requirements (i.e., accuracy and latency), as well as the features of the available sensing data. In addition, it is essential to have a unified framework to enable machine learning at different layers and components, supporting distributed learning and transfer learning, as well as a theoretical foundation of machine learning (e.g., robustness and explainable).

Integrating machine learning into radar sensing creates opportunities for novel interdisciplinary research topics, such as machine learning for radar sensing, sensing deployment, and operations; machine learning-enabled low-latency radar data analytics; machine learning-enabled sensing and decision making; and machine learning-enabled ultralow latency and highly reliable communication. Some interesting subjects include: 1) exploring the machine learning architecture, training model, and well-designed training algorithms to build highly accurate models based on a small amount of sensing data; 2) leveraging the newly received data to continually retrain the model to adapt the machine learning model to the new environment; 3) systematically studying various machine learning techniques (e.g., supervised/unsupervised learning and enforcement learning) and their use in radar sensing systems; and 4) establishing a theoretical foundation to address the uncertainty, interpretability, generalization, and security resilience of machine learning models.

7) Security and Privacy: An ISAC system consists of a number of components and multiple layers. All components and their interactions could be subject to attacks. Sensing and communication infrastructure can also be subjected to a number of threats, which tend to affect the availability, integrity, and confidentiality of the system. Therefore, it is critical to thoroughly explore various threats in the systems (e.g., attack objectives and attack techniques), design schemes to understand the impacts of the potential threats, and develop countermeasures to secure ISAC systems. For instance, one prominent threat in a sensing system is rouge and comprised devices. To this end, Liu *et al.* [148] performed a comprehensive survey on detecting and identifying IoT devices. In this work, the authors focused on reviewing the state-of-the-art machine-learning algorithms to recognize devices using passively collected wireless signal patterns and system traffic traces.

Another threat to the ISAC system is that, since sensing and communication share the same waveform, the target can also receive the same data stream for the intended communication receivers and conduct eavesdropping and even actively jam the communication channels. Thus, corresponding countermeasures should be considered in the physical layer design to prevent information from leaking to malicious sensing targets or passive radar receivers via the echoes scattered from the target. In particular, secure communication techniques, such as cost-effective cryptography and authentication, should be considered to prevent eavesdroppers from decoding the message. Furthermore, to enable the legitimate parties to carry out secret communication, artificial noise [149] can also be a viable solution. With this technique, artificial noise (signal in the null space of the receiver's channel) can be injected into the transmit signal to only degrade the eavesdroppers' channel.

The massive amounts of data collected during the sensing procedure may contain privacy-sensitive information, such as personal health data, an individual's daily routine, and habits. To this end, it is critical to understand the privacy implication of privacy disclosure and linkage threats in ISAC. As a defense, it is important to consider mechanisms, such as data perturbation, differential privacy, and secure multiparty computing schemes to systematically study the tradeoffs between privacy guarantee and utility of the data collected in ISAC. Also, the performance impact of privacy-preserving mechanisms on the ISAC system should be further investigated.

VII. Final Remarks

In this article, we conducted a comprehensive review of ISAC, including the state-of-the-art enabling techniques, applications, tools and data sets, and standardization, and outlined research challenges and future research directions. For the state-of-the-art enabling techniques, we explored existing efforts on transmit waveform design, environment modeling, sensing source, signal processing, and data processing. Regarding the applications supported by ISAC, we reviewed some key applications (human activities recognition, target localization and tracking, etc.). We also introduced some useful tools and data sets, as well as efforts toward standardization. Finally, we highlighted some challenges and provided a number of promising future research directions. We hope our efforts can provide some valuable reference for future research and development, and the progression of ISAC technologies.

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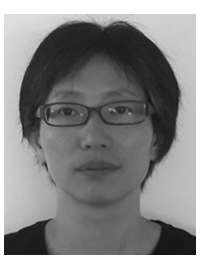

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