

Towards Integrated Sensing and Communications in IEEE 802.11bf Wi-Fi Networks

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Abstract—As Wi-Fi becomes ubiquitous in public and private spaces, it becomes natural to leverage its intrinsic ability to sense the surrounding environment to implement groundbreaking wireless sensing applications such as human presence detection, activity recognition, and object tracking. For this reason, the IEEE 802.11bf Task Group is defining the appropriate modifications to existing Wi-Fi standards to enhance sensing capabilities through 802.11-compliant devices. However, the new standard is expected to leave the specific sensing algorithms open to implementation. To fill this gap, this article explores the practical implications of integrating sensing and communications into Wi-Fi networks. We provide an overview of the support that will enable sensing applications, together with an in-depth analysis of the role of different devices in a Wi-Fi sensing system and a description of the open research challenges. Moreover, an experimental evaluation with off-the-shelf devices provides suggestions about the parameters to be considered when designing Wi-Fi sensing systems. To make such an evaluation replicable, we pledge to release all of our dataset and code to the community.

Index Terms—Wi-Fi sensing, IEEE 802.11bf, integrated sensing and communications.

I. INTRODUCTION

IN 1997, following a seven-year development process, the Institute of Electrical and Electronics Engineers (IEEE) released the first standard of the 802.11 series. The document specified the physical (PHY) and medium access control (MAC) layers for wireless local area networks operating on the *unlicensed* portion of the radio spectrum. The name *Wi-Fi* was introduced in 1999 when a group of telecommunication companies founded the Wi-Fi Alliance to ensure interoperability among IEEE 802.11 devices. Today, Wi-Fi networks are used to connect hundreds of millions of people worldwide, and the research community has suggested leveraging their ubiquitousness for *wireless sensing* applications. This entails obtaining information about objects or people in the environment as they act as radio signals reflectors, diffractors, and/or scatterers. Information is obtained by tracking changes in some quantities – referred to as *sensing primitives* – that capture the way radio signals propagate in the environment. Specifically, Wi-Fi devices continuously monitor the radio channel to properly transmit and decode data. Therefore, *Wi-Fi sensing* can reuse the information already estimated for communication purposes as sensing primitives. This way, Wi-Fi devices can act as environmental sensors, opening up a plethora of new applications such as human activity recognition, person detection and identification, human pose classification, and the Metaverse, among others [1], [2].

To make Wi-Fi sensing systems available to the general public, researchers are currently following two parallel and equally important directions. The first one is making sensing primitives available outside of the communication procedure. To this end, the new IEEE 802.11bf standard is being designed and expected to be commercialized by 2024 [3]. Concurrently, other researchers are proposing sensing algorithms for different applications. This article aims to bridge the two research lines, providing a vision of the Wi-Fi features that are key enablers for sensing (Section II), together with the approaches that can be followed to design sensing algorithms (Section III). Practical hints attained from experimental evaluations with commercial Wi-Fi devices implementing the IEEE 802.11ax standard are provided in Section IV. In Section V, an overview of the research challenges concludes the article, as summarized in Fig. 1. Overall, the discussion allows a proper understanding of the working principles behind Wi-Fi sensing through upcoming 802.11bf networks. Moreover, to the best of our knowledge, this is the first time data from commercial 802.11ax-compliant devices is considered for sensing purposes. In turn, the analysis in Section IV is the first that considers the new orthogonal frequency-division multiple access (OFDMA) modulation scheme that has been introduced with IEEE 802.11ax and is going to be adopted also in next-generation Wi-Fi networks.

II. WI-FI NETWORKS SUPPORT FOR SENSING

Wi-Fi sensing aims to detect (and possibly, track) the presence of obstacles between a transmitter and a receiver. To do so, researchers have initially considered the received signal strength indicator (RSSI) as a sensing primitive, which provides information about signal attenuation. Nowadays, most research activities are focused on the channel state information (CSI) that provides more fine-grained information about the propagation of Wi-Fi signals in the environment. Specifically, a transmitted Wi-Fi signal is affected by *multi-path propagation*, i.e., multiple copies of the signal – each associated with a different time delay and amplitude change – are collected at the receiver due to reflections, diffraction, and scattering phenomenon associated with fixed and moving objects in the environment. Hence, to properly transmit and decode the data, Wi-Fi devices need to estimate the way the wireless channel modifies the signal. Such channel characterization – referred to as the CSI – is obtained by leveraging training fields in the data packets, for which the actual decoding is known. The CSI can either refer to the channel impulse response (CIR) or the

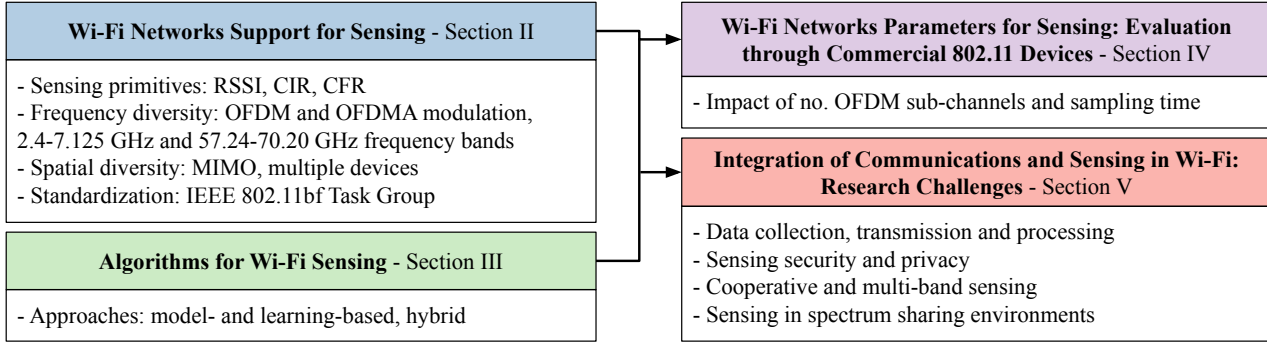


Fig. 1. High-level overview of the structure of the article.

channel frequency response (CFR). The former is a time series containing information about the delay and amplitude of each of the different paths. The latter is its frequency representation and describes how the channel modifies signals at different frequencies. Both of them can be used for sensing purposes.

A. The Role of Frequency and Spatial Diversity

Concurrently obtaining data about the propagation of radio waves characterized by different carrier frequencies (*frequency diversity*), or captured at different points in space (*space diversity*) is a crucial aspect to provide high classification accuracy and adaptation to different conditions.

As a source of frequency diversity, sensing algorithms can leverage the orthogonal frequency-division multiplexing (OFDM) and OFDMA modulation schemes adopted by Wi-Fi devices. OFDM – used before IEEE 802.11ax – leverages frequency-orthogonal radio spectrum sub-channels to increase the network throughput with respect to single-carrier modulation schemes. OFDMA – introduced with IEEE 802.11ax – allows allocating groups of sub-channels to different devices in a parallel fashion. To demodulate the collected data, OFDM/OFDMA receivers need to obtain CFR estimates for each of the sub-channels. Thus, the per sub-channel CFR is available for sensing purposes without additional computation.

Another source of frequency diversity resides in simultaneously obtaining data from multiple transmissions in the 2.4 - 7.125 GHz range, and/or in the 57.24 - 70.20 GHz range. Very recently, the Federal Communication Commission (FCC) has opened the 5.925 GHz to 7.125 GHz spectrum for unlicensed use [4]. The European Commission adopted an analogous decision in June 2021 with the release of 500 MHz at similar frequencies (5.945-6.425 MHz) [5]. These new portions of the spectrum are commonly referred to as the 6 GHz band and commercial devices operating in this band are certified by the Wi-Fi alliance as Wi-Fi 6E (extension of Wi-Fi 6). Spectrum bands above 57 GHz – millimeter wave (mmWave) – are more challenging from a communication point of view but are significantly appealing for sensing purposes as they offer wider bandwidths. IEEE 802.11ad (2012) and IEEE 802.11ay (2021) can both operate in these spectrum bands. By relying on both bands, relevant features at different granularity may be captured for sensing.

Spatial diversity can be pursued by using antenna arrays and/or performing cooperative sensing. As for the former, in

2009, IEEE 802.11n (Wi-Fi 4) introduced the multi-input, multi-output (MIMO) technology that leverages arrays of antennas to transmit multiple data streams to a user in a parallel fashion. MIMO has been refined in 2013 through IEEE 802.11ac (Wi-Fi 5) with the introduction of downlink multi-user MIMO (MU-MIMO), and in 2021 through IEEE 802.11ax that enables MU-MIMO also in the uplink direction. CFR estimates for each pair of transmitting and receiving antennas can be acquired when MIMO transmissions are used. In turn, sensing systems can gather data from the active MIMO channel sensing procedures, thus integrating spatial diversity within sensing operations. Cooperative sensing is another way to incorporate spatial diversity by combining the channel information from multiple Wi-Fi devices, thus increasing sensing granularity. On the other hand, this requires strict coordination among the devices involved in the sensing process to obtain consistent data starting from the device-specific transmission and collection schedules.

B. Standardizing Sensing Features in Wi-Fi

Today, the majority of Wi-Fi devices use the IEEE 802.11n/ac/ax standards, which provide sensing primitives as described in Section II-A. Another IEEE Task Group (TG) is working on the 802.11be amendment (Wi-Fi 7) [6], and the new features in 802.11be may also be relevant from a sensing perspective. *However, current Wi-Fi standards are intended and designed for communication purposes and do not provide the proper support for the integration of sensing functionalities.* Researchers are constrained to handcraft ad-hoc procedures to extract channel information from commercial devices, thus hindering the development and commercialization of sensing systems. Thus, extending Wi-Fi standards to support sensing becomes quintessential. Recognizing the importance of the issue, the IEEE 802.11 Working Group approved in September 2020 a Project Authorization Request (PAR) defining a new TG – called IEEE 802.11bf – that aims to define modifications to state-of-the-art 802.11 standards at both the MAC and PHY to support sensing. When 802.11bf will be finalized in September 2024, Wi-Fi will cease to be a communication-only standard and will become a *full-fledged sensing paradigm*. The IEEE 802.11bf standard is expected to enable sensing in legacy and mmWave bands and provide easier access to sensing primitives.

III. ALGORITHMS FOR WI-FI SENSING

While providing the proper support for sensing, the IEEE 802.11bf standard is not expected to define specific sensing algorithms. Conversely, the sensing primitives will be leveraged to design different sensing applications [1]. Current approaches can be categorized into *model-based*, *learning-based*, and *hybrid* strategies, as discussed next [7].

A. Model-based Approaches

This strategy leverages radio propagation models to capture the channel variations and use them as a proxy to estimate the location and the movements of targets in the environment. Model-based algorithms can be used for example to detect the presence of an object or a person by monitoring the range, Doppler, and angles spectra [8].

The frequency diversity provided by OFDM and OFDMA allows computing the distance between the device and the obstacle in the environment (range). This is obtained – similar to radar sensing – by computing the signal spectrum over the different OFDM/OFDMA sub-channels for each CFR estimate. Depending on the length of the propagation path, each copy of the transmitted signal is affected by a time delay that reflects on a frequency shift on each OFDM/OFDMA sub-channel. Therefore, peaks on the spectrum reveal the presence of obstacles and their range. Notice that the higher the bandwidth, the higher the range accuracy should be. Considering a bandwidth of 160 MHz (802.11ax devices), the range resolution is still low (about 2 meters) to be appealing for sensing. In this respect, the newly available 6 GHz and mmWave bands will be more beneficial for ranging purposes as they provide higher bandwidths [9].

The moving velocity of the sensing target can instead be estimated considering the Doppler shift induced by the movements. The estimate is obtained by computing the spectrum over subsequent transmissions with fixed inter-packet time, considering one single OFDM/OFDMA sub-channel. The spectrum captures how the frequency shifts associated with the path length vary in time. Therefore, the spectrum peaks indicate the target moving velocity. The results on the available sub-channels can be combined to increase the accuracy of the estimate [10].

Spatial diversity allows identifying the angular position of the target by analyzing the shift among the signal copies received at the different antennas, i.e., the received signal angle of arrival (AoA). The higher the number of antennas, the higher the angular position accuracy [11].

B. Learning-based and Hybrid Approaches

In general, model-based approaches do not perform well when considering a significant number of activities or gestures, and they do not generalize well to multiple subjects and environments. Learning-based approaches, instead, allow capturing relevant features directly from the unprocessed Wi-Fi CSI [7]. Learning-based techniques span from traditional machine learning algorithms, such as clustering, to advanced deep learning strategies, such as residual networks and attention mechanisms. To combine the close connection with the

physical world of model-based approaches with the level of detail that can be obtained through learning-based approaches, hybrid approaches are currently being investigated [12]. We point out that training learning-based and hybrid techniques require large datasets featuring significant domain diversity in terms of days of measurement, environments where data is collected, Wi-Fi hardware deployed, and monitored people (in the case of human sensing). This is key to designing algorithms that can generalize well over different domains, thus enabling their implementation on commercial devices [13].

IV. WI-FI NETWORKS PARAMETERS FOR SENSING: EVALUATION THROUGH COMMERCIAL 802.11 DEVICES

We analyze the impact of the sensing bandwidth and the channel sampling period on the classification accuracy. We focus on the human activity recognition task – being one of the most investigated applications for smart-home scenarios – considering the state-of-the-art approach proposed in [13]. For that, we collected a completely novel dataset – which we pledge to share with the community – entailing IEEE 802.11ax channel data captured in an indoor environment. To the best of our knowledge, our dataset represents the first collection of 802.11ax CSI data from commercial devices.

Experimental network setup. We set up an IEEE 802.11ax network with two Asus RT-AX86U Wi-Fi access points (APs). The devices exchanged Wi-Fi data over the IEEE 802.11ax channel number 157 using the OFDMA resource unit RU1-80, i.e., with a bandwidth of 80 MHz and 996 sub-channels.

CFR data collection. We used the AX-CSI tool to obtain the CFR for each packet collected by the receiver [14]. We considered an inter-packet distance of $T_c = 7.5$ ms, being reasonable for sensing applications. We asked a volunteer to perform three activities, i.e., walking and running around the room, and staying in place. We also added an “empty room” class, for a total of four classes. Note that we focus on a limited set of activities as we are mainly concerned with studying how a sensing system behaves when changing some communications parameters rather than proposing new sensing strategies. For each class, data from four different campaigns – lasting two minutes each – were collected.

CFR data processing. The CFR phase offsets associated with hardware imperfections were corrected using the approach developed in [13]. Hence, Doppler vectors were computed every time a new measurement was obtained at the receiver considering a channel observation window of 25 channel readings (the current measurement together with the 24 previous ones), and averaging over the available OFDM sub-channels (see [13]). The deep neural network (DNN) in [13] was trained as a four classes classifier. The DNN took as input $N = 256$ consecutive Doppler vectors at a time to estimate whether the person was present in the room and, in case, which activity they performed. Once trained, the DNN was used to predict the classes on CFR data never considered during training, thus allowing for a fair evaluation of the sensing performance.

Performance evaluation. A four-fold cross-validation mechanism has been used, with two campaigns used for training, one for validation, and the remainder for test. Nine different

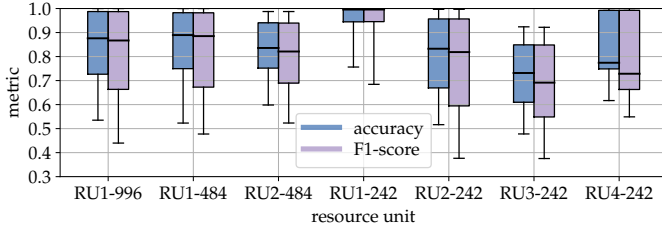


Fig. 2. Average accuracy and F1-score with different OFDMA RUs.

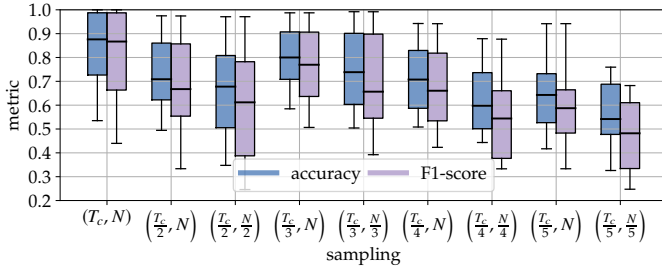


Fig. 3. Average accuracy and F1-score considering different sampling periods and number of Wi-Fi channel readings used as input for the activity classifier.

validation rounds were performed, for a total of 108 evaluation sets. The statistics of the accuracy and F1-score averaged over the 108 tests and the four classes are reported in Figs. 2-3. The bars cover the 25-75 percentile interval, the horizontal line within each bar represents the median value, and the whiskers span over the 5-95 percentile interval.

Fig. 2 shows the sensing results considering seven different OFDMA RUs as specified by the 802.11ax standard. This allows evaluating how the sensing performance changes when changing the number of OFDMA sub-channels, and, in turn, the sensing bandwidth. The RUs are identified by two numbers where the one after the dash indicates the number of sub-channels, i.e., 996, 484, or 242 for respectively 80 MHz, 40 MHz, and 20 MHz RU bandwidth. The number before the dash indicates which of the RUs characterized by the same number of sub-channels is considered, i.e., 1, 2, 3, or 4, starting from lower frequency sub-channels to higher frequency ones. The results indicate that there is not a clear link between the number of sub-channels leveraged for sensing and the sensing accuracy. This suggests that – more than blindly relying on higher bandwidths – the design of sensing applications should consider properly selecting the sub-channels that are the best for sensing purposes based on some architecture-defined metrics. The higher the number of sub-channels, the more choices are available for the selection process.

In Fig. 3 we evaluate the impact of the sampling period on the sensing performance. Each evaluation has been performed by re-sampling the sensing data at RU1-996 considering sampling periods of $T_c/2$, $T_c/3$, $T_c/4$, and $T_c/5$. We also evaluate the impact of changing the number of Doppler vectors used as input for the neural network accordingly to the sub-sampling operations, i.e., N , $N/2$, $N/3$, $N/4$, and $N/5$. The first group of bars refers to the reference metrics, i.e., without sub-sampling. We notice that the sensing performance decreases when sub-sampling the signal, even if there is not a clear trend as $T_c/3$ offers better performance than $T_c/2$. Therefore, the sampling period should be properly evaluated for each sensing

design.

V. INTEGRATION OF COMMUNICATIONS AND SENSING IN WI-FI: RESEARCH CHALLENGES

Although the research community is actively working on defining proper PHY/MAC layer modifications and algorithms to enable sensing, it is not clear how communications and sensing services will intertwine. To bridge this gap, we provide an overview of the main research challenges to the effective integration of Wi-Fi sensing and communications.

A. Data Collection, Transmission and Processing

Data collection. Either the Wi-Fi APs or devices such as smartphones, tablets, and laptops, i.e., non-AP stations (non-AP STAs), can gather sensing data (see Fig. 4 on the left). The device where to execute this phase should be selected based on the required accuracy and Wi-Fi device manufacturers will need to properly consider the sensing needs during the design phases. For example, the antenna placement should be reconsidered as external antennas provide better signal-to-noise ratio (SNR), and equally spaced antennas ease the computation of the AoA to estimate the position of targets [2].

Data processing. For this phase, Wi-Fi APs, non-AP STAs, and ad-hoc edge devices may serve as computing units. Alternatively, the processing can be offloaded to cloud services (see Fig. 4 on the right). The choice should be guided by the needed computing power and the time sensitivity of the sensing application. In general, learning-based or hybrid approaches require higher computing power due to the long training process. In this respect, the training is expected to be performed either by the application vendors or demanded to the final users. In the former case, the data is collected, processed, and stored only by the application provider thus the user is not required to collect data for training. This approach is the most convenient from a user privacy perspective. However, it may lead to decreased sensing performance as sensing is actually performed in a different scenario than the ones considered at training. The latter approach consists in providing the user with the sole learning-based architecture that will be trained with user-specific data collected on the final deployment. While this strategy would be the best in terms of the accuracy of the trained algorithm, it may be of difficult applicability as the system would not be plug-and-play. As a tradeoff between the two approaches, few shots adaptation and continual learning algorithms can be considered, and the adaptation can be performed both on the local computing facilities or remotely on the cloud managed by the vendor. The inference phase requires less computing power but still needs memory support to save the learned parameters. To this end, strategies for resource-constrained devices, such as Wi-Fi APs and non-AP STAs, are being developed. Overall, we expect that both on-site and remote computing will be available, and that end users will have access to a marketplace where to download sensing applications for their devices. Each application will have some requirements in terms of sensing data collection and support for computation, and different versions would be made available to provide broad support. Wi-Fi AP will probability

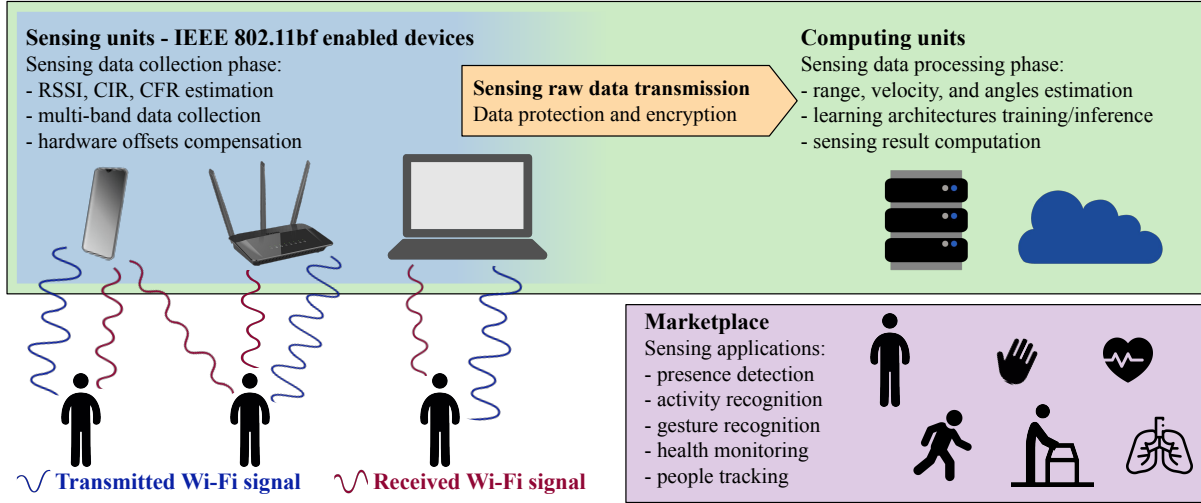


Fig. 4. Integration of sensing in Wi-Fi networks. Channel data are collected by the sensing units. Hence, the sensing application is executed on the computing units. Sensing applications can be downloaded from a marketplace.

be provided with some basic sensing features already included, with the possibility to install additional tools depending on the resource availability.

Data transmission. Depending on where the sensing data collection and the processing phases are executed, the sensing data may need to be transmitted from the sensing data collector to other local or remote entities that manage the processing, as depicted in Fig. 4. Such data transmission makes it essential to integrate some data protection and encryption strategies to prevent adversarial attacks against the sensing service. In this respect, IEEE 802.11bf introduces the protected management frames for the sensing measurement report transmission. Moreover, when data is transmitted to the cloud, some techniques should be applied to anonymize the information and prevent possible privacy issues and data leakages.

B. Sensing Security and Privacy

The pervasiveness of sensing into our everyday lives will necessarily elicit security and privacy concerns. Given the broadcast nature of the wireless channel, a malicious eavesdropper could easily capture the CSI reports and track the user’s activity without authorization. Worse yet, since Wi-Fi signals can penetrate hard objects and can be used without the presence of light, end-users may not even realize they are under attack. However, as yet, research and development efforts have been focused on improving the classification accuracy of the phenomena being monitored, with little regard to security and privacy issues. To address this point, the first important aspect is the development of DNN-based Wi-Fi sensing systems robust to adversarial machine learning techniques. Moreover, individuals should be provided the opportunity to *opt out* of sensing services, as depicted on the left side of Fig. 5. This would require the widespread introduction of reliable sensing algorithms for subject identification. Although some techniques have been proposed [1], it is unclear whether they are resilient to malicious users actively trying to impersonate other users, as shown on the right side of Fig. 5, or adverse

channel conditions, i.e., presence of noise and interference from other technologies. Identification techniques should also be tested against adversaries, either through active techniques, i.e., a device carefully jamming the sensing activity, or passive techniques, i.e., materials shielding and/or deflecting the Wi-Fi radiation. Another issue arises when the malicious entity estimates the CSI and performs sensing on ongoing Wi-Fi traffic. Here, a possible solution is to encrypt the training fields of the data packets so that only trusted devices can retrieve them and estimate the CSI. This option was already adopted in IEEE 802.11az to protect the location/ranging information from potential eavesdroppers.

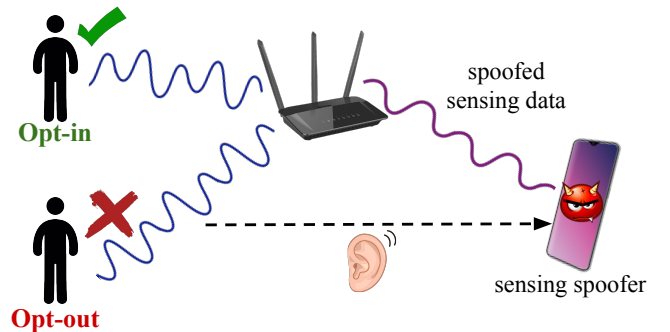


Fig. 5. Sensing security and privacy.

C. Cooperative and Multi-band Sensing

Cooperative and multi-band sensing will provide a unique opportunity to not only boost the sensing accuracy, but also to leverage the increased location awareness of blockages to design intelligent sensing-aided Wi-Fi communications that will ameliorate the performance of mmWave Wi-Fi links. For example, understanding the size and movement of blocking entities through sub-7 CSI reports could guide beam selection in the mmWave link, as shown in Fig. 6. By the same token, understanding the location of a non-AP STA by using sub-7 sensing can help reduce the overhead associated

with beam scanning and alignment. A key challenge will be to coordinate time-sensitive cooperative sensing operations among multiple Wi-Fi devices in different spectrum bands. Indeed, communication-related sensing will be extremely time-sensitive, with maximum tolerable deadlines in the order of milliseconds. To this end, a possible strategy could be to introduce control channels in the sub-7 band exclusively dedicated to the coordination of low-latency cooperative sensing operations.

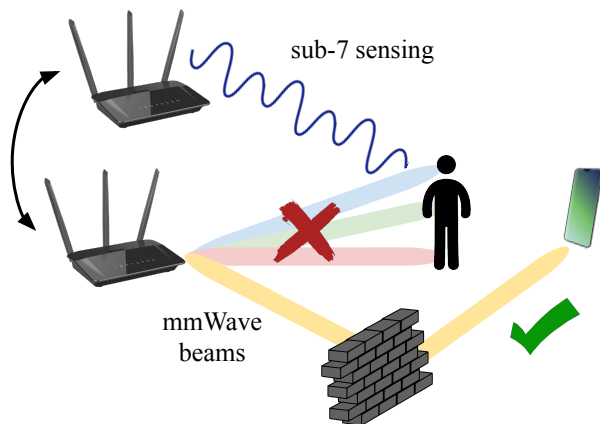


Fig. 6. Multi-band cooperative sensing-aided Wi-Fi Systems.

D. Sensing in Spectrum-Sharing Bands

From IEEE 802.11ax onward, Wi-Fi devices will share the spectrum with incumbents in the 6 GHz band, such as licensed point-to-point and satellite services, as well as other license-exempt ultra-wideband systems and 5G NR-Unlicensed. To protect incumbent services, license-exempt devices operate under restrictions such as maximum emitted power and indoor-only operation. Given the intense spectrum sharing in the 6 GHz band, further investigations should address how to make sensing robust to interference.

VI. CONCLUDING REMARKS

Sensing services are expected to be implemented within Wi-Fi networks by 2024 through the release of the IEEE 802.11bf standard. Researchers are currently working on two parallel directions that will enable integrated sensing and communication services. The Wi-Fi technological peculiarities leveraged for sensing purposes are detailed in this article, together with the approaches to developing Wi-Fi sensing algorithms. Practical lessons learned from experimental evaluations with commercial devices have also been included. Finally, we have provided an overview of the research challenges that are still open and should be addressed by the time the 802.11bf standard will be commercially available. Overall, we hope that our contribution will provide a comprehensive overview of the opportunities and challenges of Wi-Fi sensing.

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