WiFi Sensing with Channel State Information: A Survey

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With the high demand for wireless data traffic, WiFi networks have very rapid growth because they provide high throughput and are easy to deploy. Recently, Channel State Information (CSI) measured by WiFi networks is widely used for different sensing purposes. To get a better understanding of existing WiFi sensing technologies and future WiFi sensing trends, this survey gives a comprehensive review of the signal processing techniques, algorithms, applications, and performance results of WiFi sensing with CSI. Different WiFi sensing algorithms and signal processing techniques have their own advantages and limitations and are suitable for different WiFi sensing applications. The survey groups CSI-based WiFi sensing applications into three categories: detection, recognition, and estimation, depending on whether the outputs are binary/multi-class classifications or numerical values. With the development and deployment of new WiFi technologies, there will be more WiFi sensing opportunities wherein the targets may go beyond from humans to environments, animals, and objects. The survey highlights three challenges for WiFi sensing: robustness and generalization, privacy and security, and coexistence of WiFi sensing and networking. Finally, the survey presents three future WiFi sensing trends, i.e., integrating cross-layer network information, multi-device cooperation, and fusion of different sensors, for enhancing existing WiFi sensing capabilities and enabling new WiFi sensing opportunities.

CCS Concepts: • **General and reference → Surveys and overviews**; • **Hardware → Wireless devices**.

Additional Key Words and Phrases: WiFi sensing, channel state information, activity recognition, gesture recognition, human identification, localization, human counting, respiration monitoring, WiFi imaging.

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1 INTRODUCTION

WiFi has a very rapid growth with the increasing popularity of wireless devices. One important technology for the success of WiFi is Multiple-Input Multiple-Output (MIMO), which provides high throughput to meet the growing demands of wireless data traffic. Along with Orthogonal Frequency-Division Multiplexing (OFDM), MIMO provides Channel State Information (CSI) for each transmit and receive antenna pair at each carrier frequency. Recently, CSI measurements from WiFi systems are used for different sensing purposes. WiFi sensing reuses the infrastructure that is used for wireless communication, so it is easy to deploy and has low cost. Moreover, unlike sensor-based and video-based solutions, WiFi sensing is not intrusive or sensitive to lighting conditions.

CSI represents how wireless signals propagate from the transmitter to the receiver at certain carrier frequencies along multiple paths. For a WiFi system with MIMO-OFDM, CSI is a 3D matrix of complex values representing the amplitude attenuation and phase shift of multi-path WiFi channels. A time series of CSI measurements captures how wireless signals travel through surrounding

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objects and humans in time, frequency, and spatial domains, so it can be used for different wireless sensing applications. For example, CSI amplitude variations in the time domain have different patterns for different humans, activities, gestures, etc., which can be used for human presence detection [3, 24, 67, 73, 75, 83, 112, 114, 121, 148, 149, 152], fall detection [32, 68, 92, 135, 137], motion detection [23, 27, 51, 55, 126], activity recognition [6, 14, 16, 18–20, 22, 28, 63, 94, 98, 99, 102, 103, 107, 117, 120, 132], gesture recognition [2–5, 33, 48–50, 62, 64, 72, 77, 81, 85, 89, 127, 134, 140, 147], and human identification/authentication [10, 11, 34, 53, 54, 82, 96, 97, 118, 124, 133, 139]. CSI phase shifts in the spatial and frequency domains, i.e., transmit/receive antennas and carrier frequencies, are related to signal transmission delay and direction, which can be used for human localization and tracking [36, 41, 43, 52, 63, 69, 74, 76, 84, 89, 93, 97, 109, 115, 126, 130, 131, 136, 137, 148]. CSI phase shifts in the time domain may have different dominant frequency components which can be used to estimate breathing rate [1, 58, 61, 95, 101, 138]. Different WiFi sensing applications have their specific requirements of signal processing techniques and classification/estimation algorithms. To get a better understanding of existing WiFi sensing technologies and gain insights into future WiFi sensing directions, this survey gives a review of the signal processing techniques, algorithms, applications, performance results, challenges, and future trends of WiFi sensing with CSI.

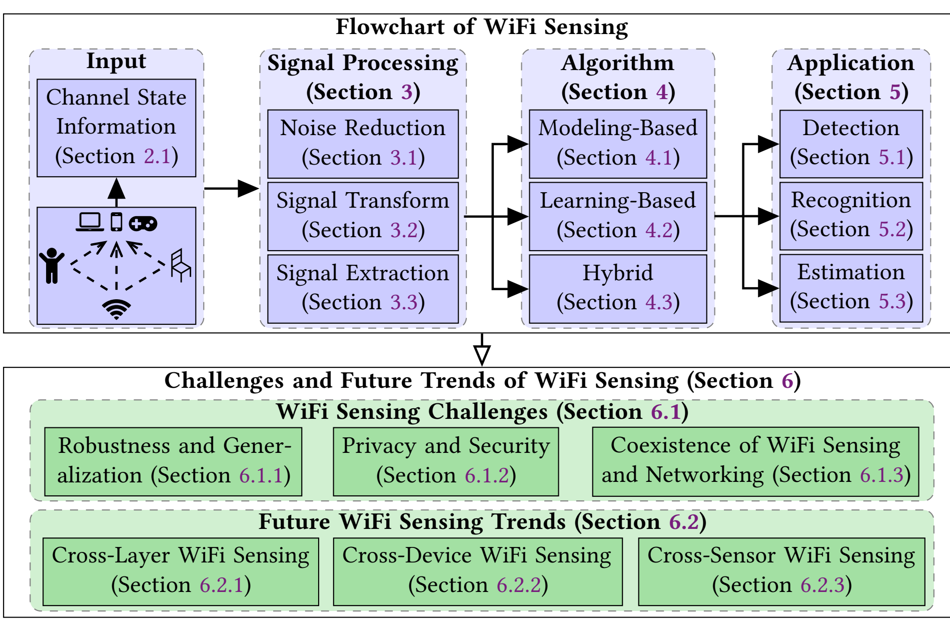


Fig. 1. Overview of WiFi sensing and paper organization.

The overview of the survey is shown in Fig. 1. The background of CSI, including mathematical models, measurement procedures, real-world WiFi models, basic processing principles, and experiment platforms, is presented in Section 2.1. Raw CSI measurements are fed to the signal processing module for noise reduction, signal transform, and/or signal extraction, as shown in Section 3. Pre-processed CSI traces are fed to modeling-based, learning-based, or hybrid algorithms to get the output for different WiFi sensing purposes, as shown in Section 4. Depending on the output types, WiFi sensing can be grouped into three categories: detection/recognition applications try to solve binary/multi-class classification problems, and estimation applications try to get the quantity values of different tasks. Section 5 summaries and compares the signal processing techniques, algorithms, output types, and performance results of different WiFi sensing applications. With the development and deployment of new WiFi systems, there will be more WiFi sensing opportunities. Section 6 gives the future trends and challenges for enhancing existing WiFi sensing capabilities and enabling new WiFi sensing purposes. In summary, we make the following contributions:

- We give a comprehensive review, including the basic principles, performance/cost comparisons, and best practice guidelines, of the signal processing techniques and algorithms of WiFi sensing in three categories: detection, recognition, and estimation.
- We present the future trends, including cross-layer network stack, multi-device cooperation, and multi-sensor fusion, for improving the performance and efficiency of existing WiFi sensing applications and enabling new WiFi sensing opportunities.

2 BACKGROUND AND RELATED WORK

2.1 Background of Channel State Information

CSI characterizes how wireless signals propagate from the transmitter to the receiver at certain carrier frequencies. CSI amplitude and phase are impacted by multi-path effects including amplitude attenuation and phase shift. Each CSI entry represents the Channel Frequency Response (CFR)

$$H(f;t) = \sum_{n}^{N} a_n(t) e^{-j2\pi f \tau_n(t)}, \tag{1}$$

where $a_i(t)$ is the amplitude attenuation factor, $\tau_i(t)$ is the propagation delay, and f is the carrier frequency [86]. The CSI amplitude $|H|$ and phase $\angle H$ are impacted by the displacements and movements of the transmitter, receiver, and surrounding objects and humans. In other words, CSI captures the wireless characteristics of the nearby environment. These characteristics, assisted by mathematical modeling or machine learning algorithms, can be used for different sensing applications. This is the rationale for why CSI can be used for WiFi sensing.

A WiFi channel with MIMO is divided into multiple subcarriers by OFDM. To measure CSI, the WiFi transmitter sends Long Training Symbols (LTFs), which contain pre-defined symbols for each subcarrier, in the packet preamble. When LTFs are received, the WiFi receiver estimates the CSI matrix using the received signals and the original LTFs. For each subcarrier, the WiFi channel is modeled by $\boldsymbol{y} = H\boldsymbol{x} + \boldsymbol{n}$, where $\boldsymbol{y}$ is the received signal, $\boldsymbol{x}$ is the transmitted signal, H is the CSI matrix, and $\boldsymbol{n}$ is the noise vector. The receiver estimates the CSI matrix H using the pre-defined signal $\boldsymbol{x}$ and received signal $\boldsymbol{y}$ after receive processing such as removing cyclic prefix, demapping, and OFDM demodulation. The estimated CSI is a three dimensional matrix of complex values.

In real-world WiFi systems, the measured CSI is impacted by multi-path channels, transmit/receive processing, and hardware/software errors. The measured baseband-to-baseband CSI is

$$H_{i,j,k} = \underbrace{\left(\sum_{n}^{N} a_n e^{-j2\pi d_{i,j,n} f_k / c}\right)}_{\text{Multi-Path Channel}} \underbrace{e^{-j2\pi\tau_i f_k}}_{\substack{\text{Cyclic Shift}\\ \text{Diversity}}} \underbrace{e^{-j2\pi\rho f_k}}_{\substack{\text{Sampling}\\ \text{Time Offset}}} \underbrace{e^{-j2\pi\eta(f_k'/f_k - 1) f_k}}_{\substack{\text{Sampling}\\ \text{Frequency Offset}}} \underbrace{q_{i,j} e^{-j2\pi\zeta_{i,j}}}_{\text{Beamforming}}, \tag{2}$$

where $d_{i,j,n}$ is the path length from the i-th transmit antenna to the j-th receive antenna of the n-th path, f_k is the carrier frequency, τ_i is the time delay from Cyclic Shift Diversity (CSD) of the i-th transmit antenna, ρ is the Sampling Time Offset (STO), η is the Sampling Frequency Offset (SFO), and $q_{i,j}$ and $\zeta_{i,j}$ are the amplitude attenuation and phase shift of the beamforming matrix. WiFi sensing applications need to extract the multi-path channel that contains the information of how the surrounding environment changes. Therefore, signal processing techniques are needed to remove the impact of CSD, STO, SFO, and beamforming, which is introduced in Section 3.

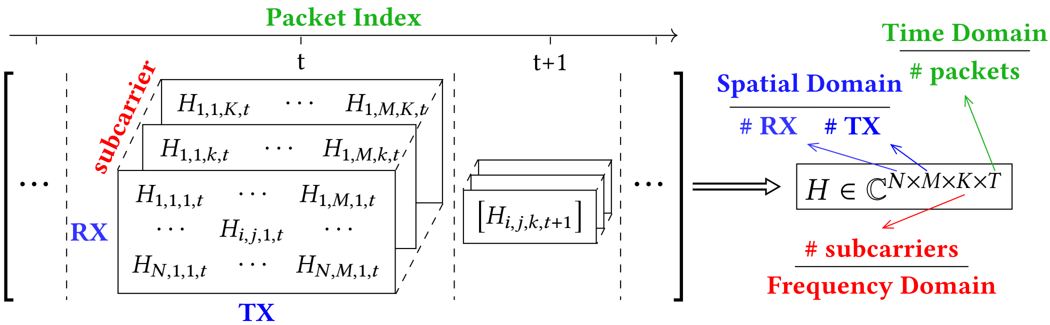


Fig. 2. The 4D CSI tensor is a time series of CSI matrices of MIMO-OFDM channels. It captures multi-path channel variations, including amplitude attenuation and phase shifts, in spatial, frequency, and time domains.

A time series of CSI matrices characterizes MIMO channel variations in different domains, i.e., time, frequency, spatial, as shown in Fig. 2. For a MIMO-OFDM channel with M transmit antennas, N receive antennas, and K subcarriers, the CSI matrix is a 3D matrix $H \in \mathbb{C}^{N \times M \times K}$ representing amplitude attenuation and phase shift of multi-path channels. CSI provides much more information than Received Signal Strength Indicator (RSSI). The 3D CSI matrix is similar to a digital image with spatial resolution of $N \times M$ and K color channels, so CSI-based WiFi sensing can reuse the signal processing techniques and algorithms designed for computer vision tasks. The 4D CSI tensor provides additional information in the time domain. CSI can be processed, modeled, and trained in different domains for different WiFi sensing purposes, e.g., detection, recognition, and estimation.

Although CSI is included in WiFi since IEEE 802.11n, it is not reported by all off-the-shelf WiFi cards. The 802.11n CSI Tool [31] is the most widely used tool for CSI measurements. It uses Intel 5300 WiFi cards to report compressed CSIs by 802.11n-compatible WiFi networks. It provides C scripts and MATLAB source code for CSI measurements and processing. OpenRF [47] is a similar tool modified based on the 802.11n CSI Tool. The Atheros CSI Tool [123] gives uncompressed CSIs using Qualcomm Atheros WiFi cards. For a 20MHz WiFi channel, the number of CSI subcarriers is 52 for the Atheros CSI Tool and 30 for the 802.11n CSI Tool. Both 802.11n CSI Tool and Atheros CSI Tool can operate at 2.4GHz and 5GHz. Software Defined Radio (SDR) platforms, such as Universal Software Radio Peripheral (USRP) [17] and Wireless Open Access Research Platform (WARP) [79], provide CSI measurements at 2.4GHz, 5GHz, and 60GHz.

2.2 Related Work

There are some surveys on specific types of WiFi sensing applications, including localization [110, 122, 128], gesture recognition [110], and activity recognition [44, 106, 110, 114, 129, 156]. In [110], the author explores device-free human localization using wireless signal reflections; the survey also discusses device-free pose estimation and fall detection. Xiao et al. [122] give a survey on both device-free and device-based indoor localization using wireless signals; the survey focuses on the models, basic principles, and data fusion techniques. Yang et al. [128] present a survey on CSI-based localization with an emphasis on the basic principles and future trends; the survey also highlights the differences between CSI and RSSI in terms of network layering, time resolution, frequency resolution, stability, and accessibility. In [44], the author gives a brief review on human motion recognition and human identification using CSI and big data analysis. Each of the four papers [106, 114, 129, 156] gives a survey on CSI-based human behavior recognition with their specific emphasis: basics and applications [106], deep learning techniques [129], data-driven and model-based approaches [156], and pattern-based and model-based approaches [114].

Table 1. Summary of Related Surveys on WiFi Sensing

Reference	Application Scope	Topic Focus
E. Wengrowski [110]	device-free localization, pose estimation, fall detection	approaches: Line-of-Sight sensors, Radio Tomographic Imaging, Through-wall RF tracking
J. Xiao et al. [122]	device-free and device-based indoor localization	models, basic principles, and data fusion techniques
Z. Yang et al. [128]	CSI-based and RSSI-based localization	basic principles and future trends; differences between CSI-based and RSSI-based solutions
S.-K. Kim [44]	motion recognition and human identification	big data analysis
D. Wu et al. [114]	human sensing	pattern-based and model-based approaches
Y. Zou et al. [156]	human behavior recognition	data-driven and model-based approaches
Z. Wang et al. [106]	human behavior recognition	basics and applications
S. Yousefi et al. [129]	human behavior recognition	deep learning techniques
This survey	All the above applications and other detection, recognition, and estimation applications	signal processing techniques, modeling-based and learning-based algorithms, applications, performance results, challenges, future trends

This survey is different from existing ones in that its scope is not limited to any specific type of WiFi sensing applications, as summarized in Table 1. The application scope of this survey includes but is not limited to human detection, motion detection, activity recognition, gesture recognition, human tracking, respiration estimation, human counting, and sleeping monitoring. The survey gives a comprehensive summary and comparison of the signal processing techniques, algorithms, and performance results of a wide variety of WiFi sensing applications. Signals processing techniques are classified into three groups: noise reduction, signal transform, and signal extraction. WiFi sensing algorithms are grouped into modeling-based and learning-based algorithms with their specific advantages and limitations. It also gives a guidance of how to select the algorithms and the corresponding signal processing techniques for different WiFi sensing applications. Finally, the survey presents future trends and challenges for enhancing existing WiFi sensing capabilities and enabling new WiFi sensing opportunities.

3 SIGNAL PROCESSING OF WIFI SENSING

This section presents signal processing techniques, including noise reduction, signal transform, and signal extraction, for WiFi sensing.

3.1 Noise Reduction

Raw CSI measurements contain noises and outliers that could significantly reduce WiFi sensing performance. Table 2 gives a summary of noise reduction techniques for WiFi sensing.

3.1.1 Phase Offsets Removal. In real-world WiFi systems, raw CSI measurements contain phase offsets due to hardware and software errors. For example, Sampling Time/Frequency Offsets (STO/SFO) are due to unsynchronized sampling clocks/frequencies of the receiver and transmitter. Some detection and recognition applications are not very sensitive to phase offsets. It is more important to get CSI change patterns. A simple solution is to use CSI phase differences of adjacent time samples or subcarriers. It cancels CSI phase offsets with the assumption that phase offsets are

Table 2. Noise Reduction Techniques for WiFi Sensing

Phase Offsets Removal	Removing phase offsets, e.g., Sampling Time/Frequency Offset, Carrier Frequency Offset, Cross-Device Synchronization Errors, Packet Detection Delay, etc., by phase difference [29, 51, 55, 100, 101, 116, 120] and (multiple) linear regression [46, 62].
Outliers Removal	Removing outliers and noises by Moving Average [7, 10, 28, 32, 49, 56, 61, 70, 91, 121, 130, 140], Median Filter [11, 80, 81, 94, 120, 137, 146], Low-Pass Filter [4, 5, 11, 19, 49, 63, 64, 80, 81, 103, 111, 120], Wavelet Filter [2, 33, 57, 58, 68, 85, 95, 117, 127, 152], Hampel Filter [10, 39, 49, 56–58, 61, 70, 73, 75, 91, 100, 101, 112, 142, 143, 152], Local Outlier Factor [32, 33, 70, 102, 127], Signal Nulling [3, 21, 35, 41, 116], and so on.

the same across packets and subcarriers. It does not give accurate phases but can recover phase change patterns which can be fed to classification algorithms.

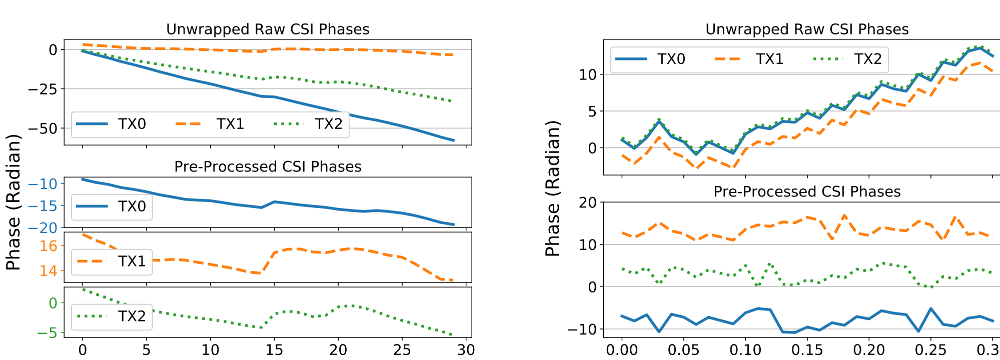
Many estimation applications require accurate phase shifts. Phase offsets introduce estimation errors for Angle-of-Arrival (AoA) and Time-of-Flight (ToF), which are used to track and localize humans and objects. SpotFi [46] removes STO/SFO by linear regression, but it does not consider different phase shifts of different transmit antennas due to CSD. This is addressed by multiple linear regression proposed in SignFi [62]. From equation (2), the measured CSI phase is

$$\Theta_{i,j,k} = \Phi_{i,j,k} + 2\pi f_\delta k \left(\tau_i + \rho + \eta \left(f'_k / f_k - 1\right)\right) + 2\pi\zeta_{i,j}, \tag{3}$$

where $\Phi_{i,j,k}$ is the CSI phase caused by multi-path effects, τ_i, ρ, η, and $\zeta_{i,j}$ are the phase offsets caused by CSD, STO, SFO, and beamforming, respectively, and f_δ is the frequency spacing of two consecutive subcarriers. The phase offsets are estimated by minimizing the fitting errors across K subcarriers, N transmit antennas, and M receive antennas

$$\widehat{\tau},\ \widehat{\omega},\ \widehat{\beta} = \arg\min_{\tau,\omega,\beta} \sum\nolimits_{i,j,k} \left(\Theta_{i,j,k} + 2\pi f_\delta k \left(i\tau + \omega\right) + \beta\right)^2, \tag{4}$$

where η, ω and β are the curve fitting variables [62]. As shown in Fig. 3a, the unwrapped CSI phases of each transmit antenna have different slopes caused by CSD. Pre-processed CSI phases $\hat{\Phi}_{i,j,k}$ are obtained by removing the estimated phase offsets, $\widehat{\tau}$, $\widehat{\omega}$, $\widehat{\beta}$, from the measured CSI phases $\Theta_{i,j,k}$.



(a) CSI Phase vs. Subcarrier Index

(b) CSI Phase vs. Sampling Time

Fig. 3. Raw CSI measurements do not capture how CSI phases change over subcarriers and sampling time.

Phase offset removal also improves performance for binary and multi-class classification applications. It recovers CSI phase patterns over subcarriers and sampling time. The raw measured CSI phases give redundant information about how CSI phases change. Phase offset removal unwraps CSI phases and recovers the lost information. As shown in Fig. 3a, raw CSI phases change periodically from $-\pi$ to π, while pre-processed CSI phases change nearly linearly in a wider range. CSI phase variations over time are also corrected. As shown in Fig. 3b, raw CSI phases of the first and second transmitting antenna change similarly, but they have very different patterns after pre-processing.

3.1.2 Outliers Removal. Moving Average and Median Filters are simple and widely used methods to remove high frequency noises. Each data point is replaced by the average or median of neighboring data points. Usually a sliding window and multiplying factors are used to give different weights, e.g., Weighted Moving Average (WMA) and Exponentially Weighted Moving Average (EWMA). Low-Pass Filters (LPF) can also remove high frequency noises assisted by signal transform methods, e.g., Fast Fourier Transform (FFT). Wavelet Filter is similar to LPFs; the major difference is that it uses Discrete Wavelet Transform (DWT) instead of FFT. Details of signal transform methods and frequency-domain filters are introduced in Section 3.2 and 3.3.

The Hampel Filter computes the median m_i and standard deviation σ_i of a window of nearby data points. If $|x_i - m_i|/\sigma_i$ is larger than a given threshold, the current point x_i is identified as an outlier and replaced with the median m_i. Sometimes the outliers are dropped rather than being replaced by the medians. Local Outlier Factor (LOF) is widely used in anomaly detection. It measures the local density of a given data point with respect to its neighbors. The local density is calculated by the reachability distance from a certain point to its neighbors. The data points with a significantly lower local density than their neighbors are marked as outliers. Signal Nulling is a special method for WiFi sensing to remove outliers. WiFi devices can used hardware, e.g., directional antennas, and software, e.g., transmit beamforming, algorithms for canceling noise signals.

3.2 Signal Transform

Signal transform methods are used for time-frequency analysis of a time series of CSI measurements. Note that the signal transform output in this scope represents the frequency of CSI change patterns rather than the carrier frequency. The summary of signal transform methods is shown in Table 3.

Table 3. Signal Transform Techniques for WiFi Sensing

Fast Fourier Transform	$X[k] = \sum_{n=1}^{N} x[n]e^{-j2\pi kn/N}$; k: frequency index. [1, 2, 10, 18, 29, 35, 39, 56, 72, 81, 82, 94, 100, 115, 120, 126, 133, 140]
Short Time Fourier Transform	$X(t,k) = \sum_{n=-\infty}^{\infty} x[n]w[n-t]e^{-jkn}$; t: time index, k: frequency index, w: window function. [10, 68, 74, 76, 77, 88, 92, 97, 127, 131, 146]
Discrete Hilbert Transform	$H[\omega] = X[\omega] \cdot (-j \cdot \mathrm{sgn}(\omega))$; ω: frequency index, $X[\cdot]$: Fast Fourier Transform, $\mathrm{sgn}(\cdot)$: sign function. [130, 146]
Discrete Wavelet Transform	approximation coefficients: $y_{1,low}[n] = \downarrow Q[\sum_{k=-\infty}^{\infty} x[k]g[n-k]]$, detail coefficients: $y_{1,high}[n] = \downarrow Q[\sum_{k=-\infty}^{\infty} x[k]h[n-k]]$; $\downarrow Q[\cdot]$: downsampling filter, $g[n]$: low-pass filter, $h[n]$: high-pass filter. [1, 2, 4, 5, 48–50, 57, 58, 68, 85, 89, 90, 95, 98–100, 117, 124, 126, 126, 127, 152]

FFT is widely used to find the distinct dominant frequencies and can be combined with a LPF to remove high frequency noises. It can also get the target signals in certain frequencies with Band-Pass Filters (BPF). For example, a time series of CSIs has different dominant frequencies when a nearby person is static or moving. FFT and BPFs can be used for human motion detection and breathing estimation, as shown in Section 3.3. Short-Time Fourier Transform (STFT) divides the input into shorter segments of equal length and computes the FFT coefficients separately on each segment, as shown in Table 3. STFT can identify the change of dominant frequencies over time by representing the time series data in both time and frequency domains. DHT adds an additional phase shift of $\pi/2$ to the negative frequency components of FFT, as shown in Table 3. It converts a time series of real-valued data to its analytic representation, i.e., a complex helical sequence. DHT is useful for analyzing the instantaneous attributes of a time series of CSI measurements.

STFT has no guarantee of good frequency resolution and time resolution simultaneously. A long window length gives good frequency resolution but poor time resolution. The frequency components can be easily identified but the time of frequency changes cannot be located. On the other hand, a short window length allows to detect when the signals change but cannot precisely identify the frequencies of the input signals. Wavelet Transform gives both good frequency resolution for low-frequency signals and good time resolution for high-frequency signals. The output of DWT can be fed to a wavelet filter to remove noises. DWT preserves mobility information in different scenarios and is more robust than Doppler phase shift [98, 99].

3.3 Signal Extraction

Signal extraction is for extracting target signals from raw or pre-processed CSI measurements. Sometimes it needs thresholding, filtering, or signal compression to remove unrelated or redundant signals. In some cases, it requires composition of multiple signal sources and data interpolation to get more information. Table 4 shows signal extraction methods widely used for WiFi sensing.

Table 4. Signal Extraction Techniques for WiFi Sensing

Filtering and Thresholding	Excluding signals with certain frequencies, power levels, etc., by filtering [1, 6, 10, 18, 20, 27–29, 48, 50, 51, 56, 72, 74, 76, 77, 80, 82, 92, 94, 97, 108, 124, 126, 132, 135, 146, 147] or thresholding [1, 2, 7, 10, 18, 20, 27, 28, 39, 41, 48, 50, 52–54, 56, 68, 77, 80, 84, 88, 89, 91–93, 95, 97–101, 103–105, 109, 113, 115, 120, 124, 130, 137, 140, 142, 143, 150, 154]; separating signals into different domains, e.g., direct/reflected paths and LoS/NLoS paths [52, 109].
Signal Compression	Removing unrelated/redundant signals by dimension reduction such as PCA [4, 5, 18, 19, 21, 48–50, 67, 68, 70, 74, 76, 77, 85, 88, 89, 97–99, 120, 124, 126, 130, 146, 148, 148, 151, 152], ICA [34, 66], SVD [21, 57, 58, 118], etc., or metrics such as self/cross correlation [24, 39, 84, 112, 115, 118, 142, 143], Euclidean distance [7, 15, 27, 40, 116], distribution function [18], and so on.
Signal Composition	Composition of signals from multiple devices [35, 46, 57, 58, 60, 81, 84, 95, 103, 119, 127, 132], carrier frequencies [87, 123, 136], and so on.

3.3.1 *Filtering and Thresholding.*

High-, low-, and band-pass filters are widely used to extract signals with certain dominant frequencies. For example, the average resting respiration rates of adults are from 12 to 18 breaths per minute. WiFi-based respiration monitoring can use a BPF to capture the impact of chest movements caused by inhalation and exhalation. It can also filter out high-frequency components caused by motions. The input signals for filtering are usually from FFT, DHT, or STFT. Butterworth filters are widely used due to its monotonic amplitude response in both passband and stopband and quick roll-off around the cutoff frequency. High-Pass Filters (HPFs) can be used to filter out signals from static objects that have relatively stable signal reflections. WiFi-based gesture recognition can use HPF to extract the target signals reflected by

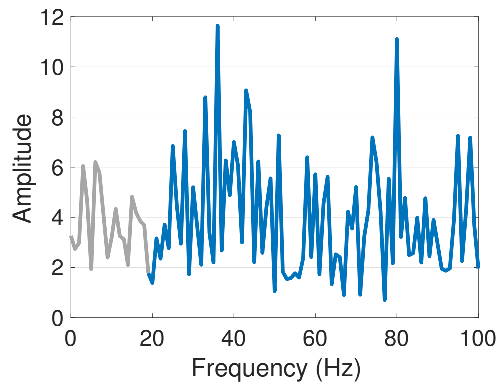
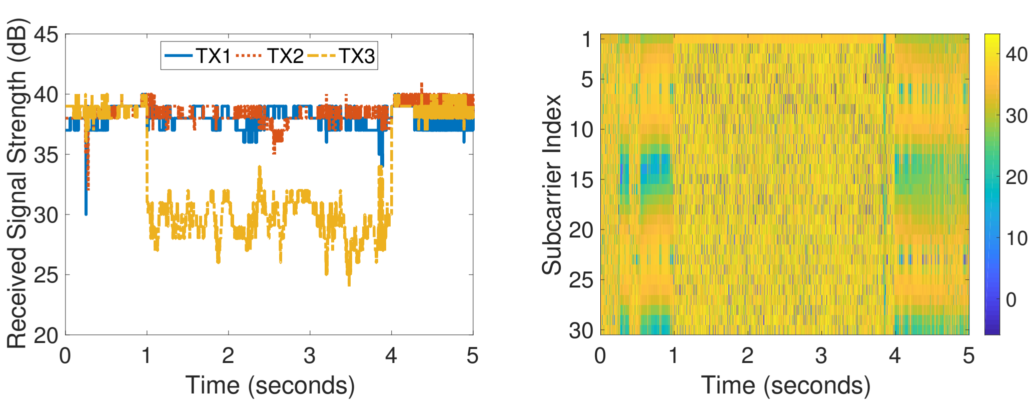


Fig. 4. High-pass filter for removing low-frequency signals that are reflected by static objects.

human movements, as shown in Fig. 4. Combined with DWT, wavelet filters are also used for outliers removal.



(a) Received Signal Strength

(b) Channel State Information Amplitude

Fig. 5. Thresholding of RSS and CSI amplitudes for extracting gesture signals. The user makes three sign language gestures during time 1 to 4 seconds.

In the time domain, thresholding can be used to extract signals with certain power levels, AoAs, ToFs, etc. As shown in equation (1), CSI is impacted by wireless signals from multi-path channels. Device-free human tracking can exclude signals of the direct path by cutting off signals with the shortest ToF. The ToFs of different paths can be calculated by Power Delay Profile (PDP), which is shown in Section 4.1. WiFi-based gesture recognition can use thresholding to exclude signals when the user is not making gestures. As shown in Fig. 5a, when the user is making gestures, the RSS of TX3 are higher than that when the user is static. The CSI amplitudes are also in different ranges when the user is making gestures, as shown in Fig. 5b. Thresholding of other metrics, e.g., CSI cross correlation, can be used for signal compression.

3.3.2 Signal Compression. Processing raw CSI measurements sometimes requires extensive computation resources. For example, $size(H) = 3 \times 3 \times 52 \times 100 \times 32/8 = 187200$ bytes for a 20MHz WiFi channel with 3TX/3RX, 52 subcarriers, and 100 CSI samples with each value represented by 32 bits. Raw CSIs can be compressed by dimension reduction techniques such as Principal/Independent Component Analysis (PCA/ICA), Singular Value Decomposition (SVD), etc., or metrics such as self/cross correlation, Euclidean distance, distribution function, etc. Signal compression can also remove redundant and unrelated information from raw CSI measurements in different domains.

PCA and ICA are widely used for feature extraction and blind signal separation. PCA uses an orthogonal transformation to convert a matrix to a set of principal components. The input is assumed to be a set of possibly correlated variables and the principal components are a set of linearly uncorrelated variables. PCA can be done by SVD or eigenvalue decomposition of the covariance or correlation matrix of the input. ICA assumes that the input signal is a mix of non-Gaussian components that are statistically independent. It maximizes the statistical independence by minimizing mutual information or maximizing non-Gaussianity, i.e., Kurtosis. Many PCA/ICA components can be discarded. For a time series of CSI matrices, redundant measurements can be removed if adjacent samples are highly correlated.

3.3.3 Signal Composition. Some WiFi sensing applications need CSIs from multiple devices, carrier frequency bands, data packets, etc. For example, SpotFi [46] requires CSIs from multiple WiFi devices and multiple data packets to accurately estimate AoAs and ToFs for decimeter-level localization. Chronos [87] requires multiple frequency bands for decimeter-level localization using a single WiFi AP. WiFi sensing algorithms using signal composition are presented in Section 4.1.

4 ALGORITHMS OF WIFI SENSING

This section presents modeling-based and learning-based algorithms for WiFi sensing. A brief summary and some examples of WiFi sensing algorithms are shown in Table 5.

4.1 Modeling-Based Algorithms

Modeling-based algorithms are based on physical theories like the Fresnel Zone model, or statistical models like the Rician fading model.

4.1.1 Theoretical Models. As shown in equation (1) in Section 2.1, CSI is a matrix of complex values representing the CFR of multi-path MIMO channels. CSI amplitude attenuation and phase shift are impacted by the distance between the transmitter and receiver and the multi-path effects including radio reflection, refraction, diffraction, absorption, polarization, and scattering. The amplitude attenuation of Free Space Propagation is

$$P_r/P_t = D_t D_r \left(\lambda/4\pi d\right)^2, \ d \gg \lambda, \tag{5}$$

where D_t and D_r are the antenna directivity of the transmitter and receiver, respectively, λ is the carrier wavelength, and d is the distance between the transmitter and receiver. It models wireless signals traveling through free space by the LoS path. In real-world scenarios, there are other objects and humans. According to equation (1), the phase shift is impacted by the time delay of each path. Phase shift is also impacted by the Doppler effect when either the transmitter or receiver moves with a speed lower than the velocity of radio waves in the medium. The observed frequency is $f = f_0(c + v_r)/(c + v_t)$, where v_r and v_t are the velocity of the receiver and transmitter, respectively, with respect to the medium, c is the velocity of radio waves, and f_0 is the original carrier frequency. Doppler phase shift is an effective model for motion detection and speed estimation.

CSI amplitude and phase are impacted by radio waves from multiple paths rather than a single path. The Fresnel Zone model divides the space between and around the transmitter and receiver into concentric prolate ellipsoidal regions, or Fresnel zones. The radius of the n-th Fresnel Zone is calculated as shown in Fig. 6. It shows how radio signals propagate and deflect off objects within the

Table 5. Summary of WiFi Sensing Algorithms

Model: $Y = f(X)$, X: CSI measurements, Y: detection, recognition, or estimation results **Algorithm:** to find the mapping function $f(\cdot)$ to detect, recognize, or estimate Y given X	
Algorithm Type	Examples
Modeling-based: (1) modeling X by theoretical models based on physical theories or statistical models based on empirical measurements; (2) inferring $f(\cdot)$ by the model of X; (3) predicting Y by the modeled function $f(\cdot)$ and measurements of X, sometimes assisted by optimization algorithms.	**Theoretical Models:** Fresnel Zone Model, Angle of Arrival/Departure, Time of Flight, Amplitude Attenuation, Phase Shift, Doppler Spread, Power Delay Profile, Multi-Path Fading, Radio Propagation: Reflection, Refraction, Diffraction, Absorption, Polarization, Scattering; **Statistical Models:** Rician Fading, Power Spectral Density, Coherence Time/Frequency, Self/Cross Correlation; **Algorithms:** MUSIC, Thresholding, Peak/Valley Detection, Minimization/Maximization
Learning-based: (1) Training: learning $f(\cdot)$ by training samples of X' and Y'; (2) Inference: predicting Y by the learned function $f(\cdot)$ and measurements of X.	**Learning Algorithms:** Decision Tree, Naive Bayes, Dynamic Time Wrapping, k Nearest Neighbor, Support Vector Machine, Self-Organizing Map, Hidden Markov Models, Convolutional/Recurrent Neural Network, Long Short-Term Memory
Hybrid: (1) modeling the problem by $Y = f(g(X))$; (2) getting $f(\cdot)$ and $g(\cdot)$ by modeling-based or learning-based algorithms; (3) predicting Y by the modeled or learned function $f(g(\cdot))$ and measurements of X.	**modeling-based** $g(\cdot) \rightarrow$ **learning-based** $f(\cdot)$: e.g., (1) extracting mobility data by Doppler Spread $\rightarrow$ recognizing gestures by k Nearest Neighbor [72]; e.g., (2) estimating position and orientation features by Channel Frequency Response $\rightarrow$ recognizing gestures by k Nearest Neighbor [89]

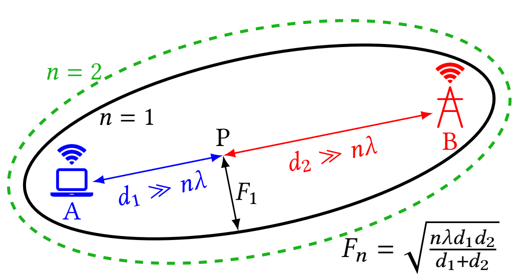
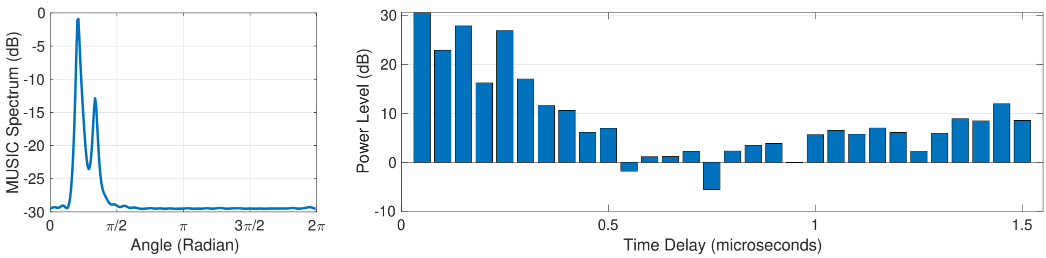


Fig. 6. Fresnel Zone Model. F_1 is the radius of the first Fresnel zone ($n = 1$) at point P.

Fresnel zone regions. The deflected signals travel through multiple paths to the receiver. Depending on the path length and the resulting amplitude attenuation and phase shift, the deflected signals lead to constructive or destructive effect at the receiver.

AoAs and ToFs are two popular models for CSI-based tracking and localization. They characterize the amplitude attenuation and phase shift of multi-path channels in terms of directions and distances. AoAs and ToFs are estimated by the phase shift or time delay from CSI measurements of an antenna



(a) AoA estimation by MUSIC

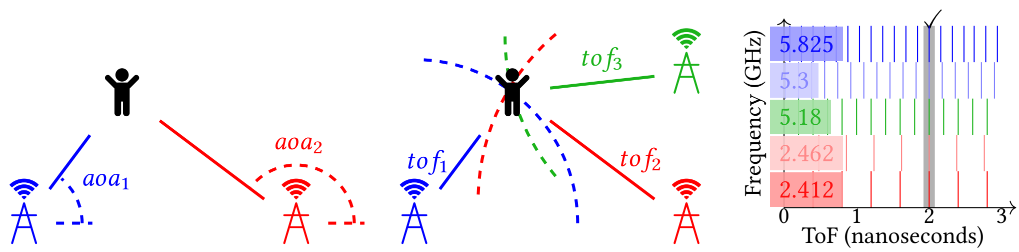
(b) ToF estimation by Power Delay Profile

Fig. 7. Estimation of Angle-of-Arrival and Time-of-Flight by CSI.

array. The Multiple Signal Classification (MUSIC) algorithm is widely used for estimating AoAs. It computes the Eigen value decomposition of the covariance matrix from CSI [46]. AoAs are calculated based on the steering vectors orthogonal to the Eigen vectors. Fig. 7a shows an example of MUSIC spectrum of different AoAs. ToFs can be estimated by Power Delay Profile (PDP) which represents the signal strength of multiple paths with different time delays. PDP is calculated by the Inverse Fast Fourier Transform (IFFT) of CSI. The corresponding PDP of CSI $H(f)$ is $h(t) = \sum_{n=1}^{N} \alpha_n \delta(t - \tau_n)$, where N is the number of paths, α_n and τ_n are the attenuation and delay of the n-th path, respectively, and $\delta(\cdot)$ is the impulse function. The norm of $h(t)$ is the signal strength of each path along which the signal arrives at the receiver with time delay t, as shown in Fig. 7b.

4.1.2 Statistical Models. Statistical models rely on empirical measurements or probability functions to characterize wireless channels. Rician fading is a stochastic model used by some WiFi sensing applications. It is a simple model for multi-path channels with a dominant path that is stronger than others. The received signal amplitude of a Rician fading channel follows a Rice distribution with $\nu^2 = K\Omega/(1+K)$ and $\sigma^2 = 2\Omega/(1+K)$, where K is the ratio between the power in the direct path and the power in the other scattered paths, and Ω is the total power, i.e., $\Omega = \nu^2 + 2\sigma^2$. CSI similarity is a widely used metric for motion-related WiFi sensing applications. It is calculated by the cross correlation of two CSI matrices [30]. Empirical measurements show that CSI similarity is a good indicator of whether the WiFi device and surrounding objects are static or moving [30]. Coherence time and coherence bandwidth, which represent the time duration or bandwidth during which the CIR is coherent, can also be used to detect the mobility status of WiFi devices.

4.1.3 Algorithms for Theoretical and Statistical Models. Threshold-based methods, peak/valley detection, and clustering are widely used modeling-based algorithms for WiFi sensing. Threshold-based methods are simple and effective for amplitude attenuation, cross correlation and distance metrics, especially for detection applications. As shown in Fig. 5, RSS and CSI amplitude are in different ranges when the user is making gestures and when the user is static. Different CSI similarity thresholds can also be used to determine the mobility status: if CSI similarity is less than 0.9, the WiFi device is moving; if it is no less than 0.9 but less than 0.99, it is environmental mobility; otherwise, it is static [30]. Threshold-based methods can also be used with other statistical metrics such as variance, Mean Absolute Deviation (MAD), Power Spectral Density (PSD), etc., and distance metrics such as Dynamic Time Wrapping (DTW), Euclidean distance, Earth Mover's Distance (EMD), etc. Peak/valley detection is widely used for phase shift and Doppler Spread for WiFi-based respiration and moving speed estimation. In these cases, CSI phases have periodic patterns, which can be detected by peak/valley detection or frequency-domain analysis.



(a) AoAs from two devices (b) ToFs from three devices (c) ToF by five frequencies [87]

Fig. 8. Localization by CSIs from multiple WiFi devices and frequency bands. Real-world applications need more than three WiFi devices, assisted by clustering or majority vote, to mitigate noises and estimation errors.

For WiFi sensing using AoAs and ToFs, it usually requires CSI measurements from multiple devices, frequency bands or data packets. SpotFi [46] uses AoAs and ToFs from multiple WiFi APs to localize the target, as shown in Fig. 8a and 8b. It also measures CSIs by multiple data packets to mitigate the impact of noises and estimation errors. Gaussian mean clustering is used to identify AoAs and ToFs from the same path but different packets. The assumption is that the direct path has the smallest ToF, so a large ToF means a low likelihood to be the direct path. SpotFi selects the path with the highest likelihood as the direct path. Chronos [87] achieves decimeter-level localization with a single WiFi AP. It estimates ToFs from multiple frequency bands such that it does not require multiple WiFi devices. As shown in Fig. 8c, a single frequency band gives a set of potential ToFs. The true ToF is identified by the Least Common Multiple (LCM) algorithm.

4.2 Learning-Based Algorithms

Binary and multi-class classification applications usually use learning-based algorithms. These algorithms try to learn the mapping function using training samples of CSI measurements and the corresponding ground truth labels.

4.2.1 Shallow Learning Algorithms. Similar to threshold-based methods, Decision Tree (DT) learning tries to find a branching rule to predict the target classes. The difference is that the branching rule of DT is learned from training data instead of hand-crafted. Naive Bayes is another technique for constructing simple and lightweight classifiers based on the Bayes' theorem. A Bayesian network is a probabilistic graphical model that represents the instances and their conditional dependencies b a Directed Acyclic Graph (DAG). Another widely used statistical algorithm is Hidden Markov Model (HMM) which can be regraded as the simplest dynamic Bayesian network. HMM represents the classification problem as a Markov process wherein the true states are hidden.

Instance-based learning algorithms, such as k Nearest Neighbor (kNN), Support Vector Machine (SVM), and Self-Organizing Map (SOM), are widely used for detection and recognition applications. These algorithms compute the distance between each testing sample and every training samples. For kNN, the testing sample is classified by the majority vote of the ground truth labels of its k nearest neighbors. SVM separates data points by a set of hyperplanes in a high dimensional space to maximize the functional margin, i.e., the distance to the nearest training data points of any class. SOM represents training samples in a low dimensional space. It is a type of neural networks using competitive learning instead of backpropagation with gradient descent as the optimization algorithm. A distance metric, such as Euclidean and Hamming distance, is needed for instance-based learning algorithms. Dynamic Time Wrapping (DTW) and data interpolation are widely used when the input is a time series of CSIs with different time durations or number of samples.

The input for shallow learning algorithms could be raw CSIs, pre-processed CSIs, or feature vectors. Since raw CSIs are usually too large and noisy, they rarely serve as the input. Pre-processed CSIs could be the filtered components of CSIs after signal transform techniques such as FFT, STFT, DWT, etc. The output of thresholding and subcarrier selection could also be the input of learning algorithms. Pre-processing helps remove noises and reduce the input size. Sometimes pre-processed CSIs are still too large and noisy for shallow learning algorithms. Feature engineering helps extract meaningful and compressed information, e.g., domain knowledge, from raw or pre-processed CSIs. It is widely used for shallow learning algorithms such as kNN and SVM. Statistical metrics are commonly used features, and dimension reduction techniques such as PCA, ICA, and SVD can also be used to extract feature vectors. Feature extraction and selection usually have a great impact on the performance of shallow learning algorithms.

4.2.2 Deep Learning Algorithms. For shallow learning algorithms, it is hard to extract and select the right features effectively and efficiently. Deep Neural Networks (DNN) address this problem by learning features automatically. DNNs require very little or none signal processing, feature engineering, and parameter tuning. DNNs are very powerful for multi-class classification applications. A DNN is organized into multiple layers. The output of the i-th layer is represented by

$$\boldsymbol{y}^{(i)} = g^{(i)}\left(\boldsymbol{W}^{(i)}\boldsymbol{x}^{(i)} + \boldsymbol{b}^{(i)}\right), \tag{6}$$

where $\boldsymbol{x}^{(i)}$ is the input, $\boldsymbol{W}^{(i)}$ is the weight matrix, $\boldsymbol{b}^{(i)}$ is the bias vector, and $g^{(i)}$ is the activation function [25]. The output of the previous layer is the input of the current layer, i.e., $\boldsymbol{x}^{(i)} = \boldsymbol{y}^{(i-1)}$. The first layer $\boldsymbol{x}^{(1)}$ is the original input, i.e., raw or pre-processed CSI measurements. The last layer $\boldsymbol{y}^{(n)}$ is the final output, i.e., binary or multi-class labels. DNNs learn the weights $\boldsymbol{W}$ and biases $\boldsymbol{b}$, using an optimization algorithm, to minimize the cost function. For example, Stochastic Gradient Descent with Momentum (SGDM) is a widely used optimization algorithm that takes small steps in the direction of the negative gradient of the loss function. To prevent overfitting, L2 regularization is usually used to add a regularization term for the weights to the loss function.

A Convolutional Neural Network (CNN) is a DNN with at least one of its layers involving convolution operations. CNNs are effective for learning local features. CNNs are relatively fast to run during training and inference due to shared kernels. CNNs are proven to have very good performance and are seen in almost all modern neural network architectures. For a sequence or a temporal series of data samples, it is usually better to use 1D CNNs or Recurrent Neural Networks (RNNs). 1D CNNs use one dimensional instead of two dimensional convolution, so they have low computational cost and good performance for simple classification problems. A major characteristic of CNNs is the lack of memory for a sequence or a time series of data points. A RNN has internal connections by iterating through the time series of input elements. Simple RNNs have the vanishing gradient problem that the network becomes untrainable as new layers added to the network [12]. Long Short-Term Memory (LSTM) is an effective and widely used architecture to address this problem. It saves the state information for later units so it prevents previous states from gradually vanishing during training. RNNs with LSTM are usually the right choice for processing a sequence or a time series of data points where temporal ordering matters. The major drawback of RNNs and LSTM is that they have very high computation cost.

A 3D CSI matrix with $size(H) = N \times M \times K$ is similar to a digital image with spatial resolution of $N \times M$ and K color channels, so WiFi sensing can reuse DNNs that have high performance for computer vision tasks. Besides, CSI data have some unique properties that are different from images and videos. For example, CSI has much smaller spatial resolutions and more frequency channels than images. Another challenge is that CSI is impacted by multi-path effects and interferences from all directions, so it contains a lot of noises and is very sensitive to environmental changes. Therefore, WiFi sensing may need new DNN architectures specifically designed for CSI data.

4.3 Hybrid Algorithms

Modeling-based and learning-based algorithms have their own advantages and limitations. For example, one of the major limitations of learning-based algorithms is overfitting, since the training process usually can only find the patterns and information that are present in the training data. Different algorithms have different requirements of signal processing techniques and are suitable for different types of WiFi sensing applications. Modeling-based algorithms are more suitable for estimation applications, and learning-based algorithms are better choices for recognition applications. For detection applications, either modeling-based or shallow learning algorithms can be the right choice. The pros and cons of *modeling-based WiFi sensing algorithms* are listed below.

Pros: (1) need very little or none training data collection, model training, and ground truth labeling
(2) need only simple algorithms, e.g., thresholding, peak/valley detection, clustering, etc.
(3) usually have low costs and run fast for both off-line analysis and real-time running

Cons: (1) need efforts for building the suitable models and finding the right model parameters
(2) need very accurate measurements and estimations, along with a lot of signal processing
(3) usually not reusable, versatile, or scalable for new tasks, scenarios, environments, etc.

Use Case: Mostly used for estimation applications which require accurate estimations of numerical values. Noise removal is crucial for modeling-based algorithms and estimation applications.

The pros and cons of *learning-based WiFi sensing algorithms* are summarized below.

Pros: (1) need very little or none signal processing
(2) evolvable: could improve when there are more training data, especially for deep learning
(3) automatic for deep learning: no need of feature engineering or learning parameter tuning
(4) reusable for deep learning: no need to restart training on new data or pre-trained models
(5) versatile for deep learning: can reuse high-accuracy pre-trained models from other tasks

Cons: (1) need a lot of efforts for training data collection and ground truth labeling
(2) need a lot of training data in different settings and easy to overfit to the training data
(3) need a lot of resources and time for training, especially for deep learning
(4) shallow learning: need feature engineering to find and select the right features
(5) instance-based learning algorithms, e.g., kNN, have high costs during the inference stage

Use Case: Mostly used for recognition applications and need very little or none signal processing.

Hybrid algorithms use both modeling-based and learning-based algorithms to address the limitations of each type of algorithms. In some cases, modeling-based algorithms are used to get coarse-grained information and then learning-based algorithms are used for fine-grained and complex tasks. For example, WiSee [72] first extracts mobility data by Doppler phase shift and then recognizes hand and body gestures by kNN. WiAG [89] first estimates the position and orientation features by CFR and then uses kNN to recognize gestures. In some cases, . For estimation applications, learning-based algorithms can be first used to detect or recognize certain events, and then modeling-based algorithms are used to estimate the quantity values of the target events.

5 APPLICATIONS OF WIFI SENSING

This section presents a summary and comparison of different WiFi sensing applications, as shown in Table 6. The signal processing techniques, algorithms, and performance results are summarized in Table 7, 8, and 9. For signal processing, NR represents Noise Reduction, ST represents Signal Transform, and SE stands for Signal Extraction. Modeling-based and learning-based algorithms are represented by M and L, respectively. Details of which algorithms require what signal processing techniques and are suitable for which types of WiFi sensing applications are also presented.

Table 6. Summary of Existing WiFi Sensing Applications

Output Type	WiFi Sensing Applications
Detection: binary classification	**Human Presence Detection** [3, 24, 67, 73, 75, 83, 112, 114, 121, 148, 149, 152]
	Human Event Detection: Fall [32, 68, 92, 135, 137], Motion [23, 27, 51, 55], Walking [126], Posture Change [57, 58], Intrusion [51, 59], Sleeping [57, 58], Keystroke [5], Driving Fatigue [16, 70], Lane Change [111], School Violence [146], Smoking [142, 143], Attack [40, 53, 54, 125], Tamper [7], Abnormal Activity [151]
	Object Detection [116]; **LoS/NLoS Detection** [113, 150]
Recognition: multi-class classification	**Activity Recognition:** Daily Activities [6, 14, 18, 20, 22, 28, 94, 98, 99, 102, 103, 107, 117], Shopping [132], Driving [16, 78], Exercising [120], Speaking [90], Acoustic Eavesdropping [108], Head & Mouth Activities [19], Walking [63]
	Gesture Recognition: Body/Head/Arm/Hand/Leg/Finger Gestures [2, 3, 33, 49, 62, 64, 72, 77, 81, 85, 88, 89, 127, 134, 140, 147], Sign Language Recognition [49, 62, 64, 81], Keystroke Recognition [4, 5, 48, 50]
	Human/User Identification [10, 11, 34, 97, 124, 133, 139]; **Human/User Authentication** [53, 54, 82, 96, 118]
	Object Recognition [111, 153, 157]; **Object Event Recognition** [66]
Estimation: quantity values of size, length, angle, distance, duration, frequency, counts, etc.	**Device-Free Human Localization/Tracking:** Position [36, 52, 69, 74, 76, 93, 109, 148], Orientation [89, 130], Motion [41, 43, 115, 130], Walking Direction [63, 115, 126, 136], Step/Gait [97, 126], Hand Drawing [84, 130, 131], Speed [137]
	Device-Based Human Localization/Tracking [46, 87, 123, 131]
	Object Localization/Tracking [60, 109, 111]; **Humidity Estimation** [141]
	Breathing/Respiration Rate Estimation: Single Person [1, 58, 61, 95, 101, 138], Multiple Persons [95, 101]; **Heart Rate Estimation** [56, 80, 100]
	Human Counting: Static Humans [15, 119], Moving Humans [9, 29, 71, 91, 144], Human Queue Length [104, 105, 111]; **WiFi Imaging** [35, 42, 153, 154]

5.1 Detection Applications

Table 7 shows the summary of WiFi-based detection applications, most of which are for human presence detection and human event detection. For event detection, most papers are on motion activities, e.g., fall and walking direction. Modeling-based algorithms, e.g., threshold-based detection, and very simple learning-based algorithms, e.g., one-class SVM are widely used. Among the 11 papers on WiFi-based human detection, 5 papers use SVM and 3 papers use threshold-based detection. For the remaining 31 papers, 9 of them use one-class SVM as the classifier. Theoretical and statistical models are usually very sensitive to noises and outliers. Noise reduction is usually needed for modeling-based algorithms such as threshold-based detection. The Hampel filter, wavelet filter, LOF are popular choices. Detection problems are relatively simple to solve and sometimes have no clear borderline between signal extraction techniques and the classification algorithm. After some signal extraction techniques such as LPFs and thresholding, the detection result can be directly derived without further detection or classification algorithms. Several papers use PCA to filter out redundant information. Since binary classification problems usually do not need extensive input data, detection applications usually do not need signal compression or feature extraction.

Table 7. Summary of WiFi Sensing: Detection Applications

Reference	Signal Processing	Algorithm	Application	Performance
Wi-Vi [3]	NR: Signal Nulling	M: AoA	Moving Human Detection; Gesture Decoding	Human Detection: 85% to 100% (3 humans); Gesture Decoding: 93.75% (6-7m), 75% (8m), 0 (9m)
Gong-2016 [24]	N/A	M: Rician Fading, Cross-Correlation	Human Detection	False Negative: <5%; False Positive: <4%
Palipana-2016 [67]	SE: Interpolation, Kernel PCA	M: Threshold-Based Detection, Rician Fading	Human Detection	True Positive: 90.6%
PADS [73, 75]	NR: Phase Offset, Hampel Filter	L: One-Class SVM	Human Detection	True Positive Rate: >93%
PeriFi [83]	NR: Phase Offsets (PDD, STO)	M: AoA, ToF, MUSIC; L: One-Class SVM	Human Detection	Accuracy: 96.7%
DeMan [112]	NR: Hampel Filter, Linear Fitting, Least Median Squares; SE: Correlation Matrix	M: Sinusoidal Model, Nelder-Mead Searching	Moving & Stationary Human Detection	Detection Rate: 94%/92% (moving/stationary)
Xiao-2015 [121]	NR: WMA	M: Threshold-Based Detection	Human Detection	N/A
Zhou-2017 [148]	NR: Density-Based Spatial Clustering; SE: PCA	L: SVM Classification & Regression	Human Detection & Localization	Detection Accuracy: >97%, Localization Error: 1.22m/1.39m (lab/meeting room)
Zhou-2014 [149]	SE: Feature Extraction	M: EMD, Fingerprinting, Threshold-Based Detection	Human Detection	Average FPR/FNR: 8%/7% (fingerprinting), ∼10% (threshold)
R-TTWD [152]	NR: Hampel Filter, Wavelet Filter; ST: DWT; SE: PCA, Interpolation, Feature Extraction	L: Majority Vote, One-Class SVM	Moving Human Detection	True Positive/True Negative: >99%
WiFall [32]	NR: WMA, LOF	L: kNN, One-Class SVM	Fall Detection	Detection Precision: 87%
FallDeFi [68]	NR: Wavelet Filter; ST: DWT, STFT; SE: PCA, Interpolation, Subcarrier Selection, Thresholding	M: Power Burst Curve; L: One-Class SVM	Fall Detection	Accuracy: 93%/80% (same/different testing environments)
RT-Fall [92]	ST: STFT; SE: BPF, Interpolation, Feature Extraction, Thresholding	M: Amplitude Attenuation, Phase Shift; L: One-Class SVM	Fall Detection	True Positive Rate: 91%, True Negative Rate: 92%
Anti-Fall [135]	SE: Interpolation, LPF, Threshold-Based Sliding Window	M: Amplitude Attenuation, Phase Shift; L: One-Class SVM	Fall Detection	Precision: 89%, False Alarm Rate: 13%
WiSpeed [137]	NR: Median Filter; SE: ℓ_1 Trend Filter, Thresholding	M: Multi-Path Scattering, Statistical Modeling, Peak Detection	Fall Detection & Speed Estimation	Fall Detection: 95%, Mean Error: 4.85%/4.62% (device-free/-based)
MoSense [27]	SE: LPF, Euclidean Distance, Thresholding	M: CFR; L: Binary Classification	Motion Detection	Accuracy: 97.38%/93.33% (LoS/NLoS, 5 activities)
Liu-2017 [55]	NR: Phase Difference; SE: Signal Isolation by Skewness	M: CIR; L: One-Class SVM	Motion Detection	Motion Detection Rate: 90.89%
FRID [23]	N/A	M: CFR, Coefficients of CSI Phase Variation	Motion Detection	Precision: 90%
AR-Alarm [51]	SE: Interpolation, BPF, Duration-Based Filter	M: Phase Difference; L: Binary Classification	Motion & Intrusion Detection	True Positive Rate: 98.1%/97.7%
SEID [59]	SE: Signal Compression by CSI Amplitude Variance	M: CFR; L: HMM	Intrusion Detection	Precision: 98%

(Continued)

Table 7 Continued

Reference	Signal Processing	Algorithm	Application	Performance
WiStep [126]	NR: Long Delay Removal; ST: FFT, IFFT, DWT; SE: Butterworth BPF, PCA, Subcarrier Selection	M: Multi-Path Fading, CIR, Short-Time Energy, Peak Detection, Threshold-Based Detection	Walking Detection & Step Counting	Walking Detection: 96.41%/1.38% (TPR/FPR); Step Counting: 90.2%/87.59% (laboratory/classroom)
Wi-Sleep [57, 58]	NR: Hampel Filter, Wavelet Filter; ST: DWT; SE: Interpolation, Subcarrier Selection by Periodicity & SVD, Multiple TX-RX Pairs	M: CFR	Respiration Rate & Apnea Estimation; Posture Change Detection	Respiration Rate Estimation: 85%; Posture Change Detection: 83.3%; Apnea Estimation: 89.8%
WiKey [4, 5]	NR: LPF, PCA; ST: DWT	L: kNN+DTW	Keystroke Detection & Recognition	Detection: 97.5%; Recognition: 96.4% (37 keys)
LiveTag [21]	NR: Signal Nulling; SE: PCA	M: AoA, MUSIC, SSP, SVD, Maximum Likelihood	Touch Detection	Missed Detection Rate: <3% to 28% (LoS), <3% to 14% (NLoS)
Bagci-2015 [7]	NR: MA; SE: Euclidean/ Mahalanobis Distance, EMD, Thresholding	M: Received Signal Strength	Tamper Detection	True Positive Rate: 53%
Liu-2018 [53, 54]	NR: Temporal Bias, De-Correlation Filter, Frequency/Temporal Smoothing; SE: Thresholding, k Means	M: Coherence Time; L: One-Class SVM	Attack Detection, User Authentication	Average Attack Detection Ratio: 92%; Authentication Accuracy: 91% (static), 70.6% to 93.6% (mobile)
CSITE [40]	SE: Merging Adjacent Samples	M: Euclidean Distance, Mean Standard Variance, Threshold-Based Detection	Spoofing Attack Detection	False Positive Rate: <4%, False Negative Rate: <4.5%
SecureArray [125]	NR: Random Phase Perturbation	M: AoA, Coherence Time, Threshold-Based Detection	Spoofing Attack Detection	Detection Rate: 100%, False Alarm Rate: 0.6%
WiFind [70]	NR: Hampel Filter, LOF, MA; SE: PCA	L: One-Class SVM	Driver Fatigue Detection	Detection Rate: 82.1%
WiTraffic [111]	NR: Butterworth LPF	L: Threshold-Based Detection, SVM, EMD	Traffic Monitoring	Lane Detection: 95%; Vehicle Recognition: 96%; Speed Error: 5mph
Smokey [142, 143]	NR: Hampel Filter; SE: Interpolation, Antenna Selection, Thresholding	M: Temporal/Frequency Correlation, Peak Detection	Smoking Detection	True Positive Rate: 92.8%, False Alarm Rate: 2.3%
Wi-Dog [146]	ST: DHT, STFT; SE: PCA, Butterworth BPF, Antenna/Subcarrier Selection	M: Doppler Shift, Wavelet Entropy, Median Filter, Thresholding; L: One-Class SVM	School Violence Detection	TPR: 85%/94%, FPR: 11%/10% (classroom/corridor)
MAIS [20]	ST: Linear Transform; SE: LPF, Outlier Filter, Thresholding, Eigen Values	L: kNN	Human Counting, Activity Detection & Recognition	Anomaly Detection: 98.04%, Human Counting: 97.21%, Activity Recognition: 93.12%
NotiFi [151]	SE: PCA	L: Nonparametric Bayesian Model, Dynamic Hierarchical Dirichlet Process	Abnormal Activity Detection	Average Accuracy: 89.2%/ 85.6%/75.3% (LoS/NLoS/through-wall)
PhaseU [113]	NR: Linear Fitting; SE: Thresholding, Antenna Selection	M: Multi-Path Reflections, Diffractions and Refractions	LoS/NLoS Detection	Detection Rate: >94%/80% (static/mobile)
LiFi [150]	NR: CFO; ST: IFFT; SE: Normalization, Thresholding	M: CIR, Rician Fading, PDP, Skewness	LoS/NLoS Detection	Accuracy: 90.4%; False Alarm Rate: 9.34%
Wi-Metal [116]	NR: Interference Nulling by Phase Difference	M: Radio Reflection; L: k Means, Euclidean Distance	Metal Detection	Accuracy: 90%; False Alarm Rate: 10%

Table 8. Summary of WiFi Sensing: Recognition Applications

Reference	Signal Processing	Algorithm	Application	Performance
Wi-Chase [6]	SE: LPF, Modulation Filter	M: Path Loss, PDP; L: kNN, SVM	Activity Recognition	Recognition Accuracy: 97% (3 activities)
WIBECAM [14]	N/A	M: PDP, Autoregressive Model, PSD	Activity Recognition	Recognition Accuracy: 73% to 100% (4 activities)
BodyScan [18]	ST: FFT; SE: Butterworth LPF, PCA, Thresholding	M: PSD, Statistical Distribution; L: SVM	Activity Recognition, Breathing Monitoring	Activity Recognition Accuracy: 72.3% (5 activities), Breathing Rate Accuracy: 97.4%
MAIS [20]	ST: Linear Transform; SE: LPF, Outlier Filter, Thresholding, Eigen Values	L: kNN	Human Counting, Activity Detection & Recognition	Anomaly Detection: 98.04%, Human Counting: 97.21%, Activity Recognition: 93.12%
DFLAR [22]	N/A	L: Sparse Auto-Encoder Neural Network	Activity Recognition	Recognition Accuracy: 90% (8 activities)
HuAc [28]	NR: Outlier Filter, WMA; SE: LPF, Thresholding, k Means	L: SVM	Activity Recognition	Recognition Accuracy: 93% (16 activities)
EI [39]	NR: Hampel Filter; ST: FFT; SE: Thresholding	L: Correlation, CNN	Activity Recognition	Accuracy: <75% (10 users, 6 activities, 3 rooms)
Wang-2018 [94]	NR: Median Filter, Linear Fitting; ST: FFT; SE: LPF, Feature Extraction	M: Coherence Histogram; L: SOM, Softmax Regression	Activity Recognition	Recognition Accuracy: >85%
CARM [98, 99]	NR: CFO; ST: DWT; SE: Thresholding, PCA, Feature Extraction	L: HMM	Activity Recognition	Recognition Accuracy: >96% (8 activities)
Wang-2015 [102]	NR: Gaussian Filter, LOF; SE: k Means, Feature Selection	M: Free Space Propagation Model; L: DTW, SVM	Activity Recognition & Fall Detection	Activity Recognition: 80% (13 activities); Fall Detection: 95.2%
E-eyes [103]	NR: LPF, MCS Filter; SE: EMD, Thresholding, Clustering, Multiple Links	L: Multi-Dimensional DTW, Pattern Matching	Activity Recognition	Average Recognition Accuracy: 90%/95% (single device/multiple devices, 13 activities)
Wei-2015 [107]	NR: Exponential Smoothing	L: Sparse Representation	Activity Recognition	Recognition Accuracy: <90% (8 activities)
ARM [117]	NR: CFO, Wavelet Filter; ST: DWT	L: DTW, HMM	Activity Recognition	Average Accuracy: >75% (6 activities)
Zeng-2015 [132]	SE: BPF, Feature Extraction, Multiple APs	M: CFR; L: DT, Simple Logistic Regression	Shopper Activity Recognition	Average Accuracy: 89.6%/94.75 (entrance/in store, 4 activities)
WiDriver [16]	SE: Signal Compression by Back Propagation Neural Network	M: Fresnel Zone Model; L: Finite Automata	Driver Activity Recognition	Recognition Accuracy: 96.8% (11 postures), 90.76% (7 activities)
HeadScan [19]	SE: Butterworth LPF, PCA	L: Sparse Representation, ℓ_1 Minimization	Head & Mouth Activity Recognition	Recognition Accuracy: 86.3% (5 activities)
SEARE [120]	NR: LPF, Median Filter, PCA Filter; ST: FFT; SE: Thresholding	L: First-Order Difference, DTW	Exercise Activity Recognition	Average Accuracy: 97.8%/91.2% (LoS/NLoS, 4 activities)
WiSome [127]	NR: LOF, Wavelet Filter; ST: DWT, STFT; SE: Locally Linear Embedding, Multiple TXs	M: Doppler Shift, Thresholding; L: kNN, SVM	Motion Direction Recognition	Average Accuracy: 95.4%/95.9%/95.5% (threshold-ing/kNN/SVM)
APsense [134]	SE: Feature Extraction	L: Naive Bayes, DT	Motion Recognition	Average TPR: 74.8% (decision tree), 56.8% (naive bayes)

(Continued)

Table 8 Continued

Reference	Signal Processing	Algorithm	Application	Performance
WiDance [77]	ST: STFT; SE: Antenna Selection, Butterworth BPF, PCA, Thresholding	M: Doppler Shift, Rule-Based Classification	Motion Direction Recognition	Accuracy: 92% (9 motion directions)
Maheshwari-2015 [63]	NR: LPF; SE: Cumulative MSD	L: DT	Gait Rate Classification	Accuracy: <60% (3 speeds), >90% (2 speeds)
WiHear [90]	NR: Butterworth BPF; ST: IFFT, DWT	M: PDP, Multi-Path Reflection; L: DTW, Pattern Matching	Speaking Recognition	Accuracy: 91%/74% (1 person/3 persons, <6 words)
ART [108]	NR: Averaging; SE: BPF	M: Wireless Vibrometry	Acoustic Eavesdropping	Recognition Accuracy: 80% (distance<4m)
WiGest [2]	NR: Wavelet Filter; ST: FFT, DWT; SE: Thresholding	L: Pattern Matching	Gesture Recognition	Recognition Accuracy: 87.5%/96% (1 AP/3 APs, 7 gestures)
Wi-Vi [3]	NR: Signal Nulling	M: AoA	Moving Human Detection; Gesture Decoding	Moving Human Detection: 85% to 100% (3 humans); Gesture Decoding: 93.75% (6-7m), 75% (8m), 0 (9m)
WiG [33]	NR: Birge-Massart Filter, Wavelet Filter, LOF	L: SVM	Gesture Recognition	Recognition Accuracy: 92% (LoS), 88% (NLoS)
WiSee [72]	NR: CFO; ST: FFT; SE: BPF, Interpolation	M: Doppler Shift; L: Pattern Matching	Gesture Recognition	Average Accuracy: 94% (9 gestures)
WiFinger [85]	NR: Wavelet Filter, Butterworth BPF; ST: IFFT, DWT; SE: PCA, Subcarrier Selection	L: Pattern Matching, Multi-Dimensional DTW	Finger Gesture Recognition	Accuracy: 93% (8 finger gestures)
WiMU [88]	ST: STFT; SE: PCA, Thresholding	M: Threshold-Based Detection, Pattern Matching	Multi-User Gesture Recognition	Accuracy: 95.0%, 94.6%, 93.6%, 92.6%, 90.9% (2, 3, 4, 5, 6 concurrent gestures)
WiAG [89]	NR: Butterworth Filter; ST: DWT; SE: PCA, Thresholding, Extrapolation	M: CFR; L: kNN	Gesture Recognition	Accuracy: 91.4% (6 gestures)
Mudra [140]	NR: MA, Finite Impulse Response Filter; ST: FFT, IFFT; SE: Thresholding	L: DTW	Finger Gesture Recognition	Average Accuracy: 96% (9 finger gestures)
DeNum [147]	SE: BPF Feature Extraction	M: Threshold-Based Sliding Window; L: NN, SVM	Gesture Recognition	Average Accuracy: 94% (10 finger postures)
WiFinger [49]	NR: Hampel Filter, LPF, WMA; ST: DWT	M: CFR, PCA; L: kNN+DTW	Sign Language Recognition	Recognition Accuracy: 90.4% (9 hand postures)
SignFi [62]	NR: STO/SFO, Multiple Linear Regression	L: CNN	Sign Language Recognition	Accuracy: 94.8% (276 signs, 1 user, lab+home), 86.6% (150 signs, 5 users, lab)
Melgarejo-2014 [64]	NR: LPF; SE: Subcarrier Selection by Similarity	L: kNN+DTW	Sign Language Recognition	Accuracy: 84% (14 signs, car), 92% (25 signs, wheelchair)
WiSign [81]	NR: Median Filter, LPF; ST: FFT; SE: Subcarrier Selection, Multiple RXs	L: SVM, Majority Vote	Sign Language Recognition	Mean Accuracy: 93.8% (5 sign gestures)
WiKey [4, 5]	NR: LPF, PCA; ST: DWT	L: kNN+DTW	Keystroke Detection & Recognition	Detection: 97.5%; Recognition: 96.4% (37 keys)
ClickLeak [48]	ST: DWT; SE: LPF, PCA, Thresholding, k Means	L: kNN+DTW	Keystroke Recognition	Recognition Accuracy: 83% (10 keys)

(Continued)

Table 8 Continued

Reference	Signal Processing	Algorithm	Application	Performance
WindTalker [50]	SE: LPF, PCA, Thresholding; ST: DWT	M: CFR; L: DTW	Keystroke Recognition	Accuracy: 81.8%/73.2%/ 64% (Xiaomi/Nexus/ Samsung, 10 numbers)
Rapid [10]	NR: CFO, Hampel Filter, MA; ST: FFT, STFT; SE: Butterworth LPF, Thresholding	M: CFR; L: SVM	Human Identification	Identification Accuracy: 82% to 92% (2 to 6 people)
NiFi [11]	NR: Butterworth LPF, Median Filter; SE: Sequence Similarity	L: Pattern Matching, HMM	User Identification	True Positive Rate: 90.83% (4 devices)
WFID [34]	NR: Threshold-Based Filter; SE: PCA	M: Doppler Shift, Radio Scattering; L: SVM	Human Identification	Identification Accuracy: 93.1% (6 subjects), 91.9% (9 subjects)
WifiU [97]	NR: CFO; ST: STFT; SE: Gaussian LPF, Thresholding, PCA	L: SVM, One-vs-All Classifiers	Human Recognition	Recognition Accuracy: 79.28%/89.52%/93.05% (top-1/-2/-3, 50 subjects)
FreeSense [124]	ST: DWT; SE: PCA, Butterworth LPF, Feature Extraction, Thresholding	L: Mean Absolute Deviation, DTW, kNN	Human Identification	94.5% to 88.9% (2 to 6 users)
WiWho [133]	NR: Distant Multi-path Removal; ST: FFT; SE: Feature Extraction	M: CFR, CIR, Peak-Valley Detection; L: DTW, DT	Human Identification	92% to 80% (2 to 6 users)
WiFi-ID [139]	NR: Silence Removal; SE: Feature Extraction	L: Sparse Representation	Human Identification	N/A
Liu-2018 [53, 54]	NR: Temporal Bias, De-correlation Filter, Frequency/Temporal Smoothing; SE: k Means, Thresholding	M: Coherence Time; L: SVM	Attack Detection, User Authentication	Average Attack Detection Ratio: 92%; Authentication Accuracy: 91% (static), 70.6% to 93.6% (mobile)
Shi-2017 [82]	ST: FFT; SE: BPF, Subcarrier Selection	L: Neural Network with Auto-Encoder, SVM	User Authentication	Accuracy: 94%/91% (walking/stationary, 11 subjects)
PriLA [96]	N/A	M: CFO, DTW	User Authentication	Average Accuracy: 93.2%
TDS [118]	SE: Feature Extraction by SVD	L: Pearson Correlation, Max-Weighted Bipartite Matching	User Authentication	Error Rate: <7% (authenticate distance=5cm)
WiTraffic [111]	NR: Butterworth LPF	L: Threshold-Based Detection, SVM, EMD	Traffic Monitoring	Lane Detection: 95%; Vehicle Recognition: 96%; Speed Error: 5mph
Ulysses [153]	NR: Majority Vote	M: Specular Reflection, AoA, AoD, Threshold-Based Detection	Object Recognition & WiFi Imaging	Top-3 Accuracy: 100% (11 objects); imaging error: <8cm/1 degree (width/orientation)
TagFree [157]	SE: Feature Extraction	M: Spectral Regression Discriminant Analysis, Random Subspace Method, LDA	Object Recognition	Average Accuracy: 96%/75%/57% (1/2/3 objects, same location, 6 objects)
Ohara-2017 [66]	SE: Signal Separation by ICA	M: CNN, RNN, HMM, LSTM	Object Event Recognition	Average Precision: 81.7%, Recall: 92.5%, F-score: 85.8%

Table 9. Summary of WiFi Sensing: Estimation Applications

Reference	Signal Processing	Algorithm	Application	Performance
LiFS [93]	SE: Thresholding	M: Fresnel Zone Model, DTW, Gradient Descent, Genetic Algorithm	Device-Free Human Localization	Median Accuracy: 0.5m (LoS), 1.1m (NLoS)
Zhou-2017 [148]	NR: Density-Based Spatial Clustering; SE: PCA	L: SVM Classification/Regression	Presence Detection & Localization	Presence Accuracy: >97%, Localization Error: 1.22m/1.39m (lab/meeting room)
IndoTrack [52]	NR: Removing Random Phase Offset by Conjugate Multiplication; SE: Isolating Direct Path Signals, Thresholding	M: Doppler Shift, AoA, MUSIC	Human Tracking	Median Tracking Error: 35cm
Widar [74, 76]	ST: STFT; SE: Butterworth BPF, PCA	M: Doppler Shift, Path Length Change Rate, Searching with Least Fitting Error	Human Tracking	Median Location Error: 25cm/38cm (with/without initial positions); Median Velocity Error: 13%
WiDeo [41]	NR: Distance-Based Thresholding, Full Duplex Interference Nulling	M: AoA, ToF, Amplitude; Kalman Filter, Compressive Sensing	Motion Tracking	Median Error: <7cm for 5 humans
QGesture [130]	NR: CFO, SFO, PBD, MA; ST: DHT; SE: Interpolation, Linear Regression, PCA, Thresholding	M: Multi-Path Propagation, CIR	1D & 2D Motion Tracking	Average Distance Accuracy: 3cm/3.7cm (1D/2D); Average Direction Error: 5%/15 degrees (1D/2D)
WiDir [115]	NR: Cross-Correlation Denoising, Polynomial Smoothing Filter; ST: FFT; SE: Thresholding	M: Fresnel Zone Model, Phase Shift, Radio Reflection/Diffraction	Moving Direction Estimation	Median Error: <10 degrees
WiStep [126]	NR: Long Delay Removal; ST: FFT, IFFT, DWT; SE: Butterworth BPF, PCA, Subcarrier Selection	M: CIR, Short-Time Energy, Peak Detection, Threshold-Based Detection	Walking Detection & Step Counting	Walking Detection: 96.41%/1.38% (TPR/FPR); Step Counting: 90.2% (lab), 87.59% (classroom)
Zhang-2017 [136]	SE: Multiple Carrier Frequencies	M: Fresnel Zone Model	Walking Direction Estimation	Median Error: 10 degrees
WiDraw [84]	SE: Thresholding, Multiple TXs, Transmitter Selection by CSI Correlation	M: AoA, MUSIC	Hand Tracking	Hand Tracking Error: <5cm; Handwriting Accuracy: 91%
WiSpeed [137]	NR: Median Filter; SE: ℓ_1 Trend Filter, Thresholding	M: Multi-Path Scattering, Statistical Modeling, Peak Detection	Speed Estimation & Fall Detection	Mean Error: 4.85%/4.62% (device-free/-based), Fall Detection: 95%
SpotFi [46]	NR: Sampling Time Offset; SE: Signal Isolation, Multiple Packets and Transmitters	M: AoA, ToF, MUSIC, CSI Smoothing, Gaussian Mean Clustering	Device-Based Localization	Median Localization Accuracy: 40cm
Chronos [87]	NR: Phase Offsets, PDD; SE: Multi-Path Separation, Multiple Frequency Bands	M: PDP, ToF, Least Common Multiple, Quadratic Optimization	Device-Based Localization	Median Distance Error: 14.1cm/20.7cm (LoS/NLoS)
Splicer [123]	ST: IFFT; SE: Multiple Carrier Frequencies	M: PDP, MUSIC	Device-Based Localization	Median Error: 0.95m
AAMouse [131]	NR: Maximal Ratio Combining; ST: STFT; SE: Kalman Filter	M: Doppler Shift	Device-Based Tracking	Median Error: 1.4cm (2 speakers), 2.5cm (1 speaker+WiFi)

(Continued)

Table 9 Continued

Reference	Signal Processing	Algorithm	Application	Performance
BikeLoc [60]	SE: Multiple TXs	M: AoA	Bike Localization	Median Error: 45cm (2 APs); 18.1cm (8 APs)
mTrack [109]	SE: Direct Component Filter, Thresholding	M: Phase Shift, Radio Reflection/Diffusion	Object Tracking	Median Tracking Error: 6.5mm
WiTraffic [111]	NR: Butterworth LPF	L: Threshold-Based Detection, SVM, EMD	Traffic Monitoring	Lane Detection: 95%; Vehicle Recognition: 96%; Speed Error: 5mph
WiHumidity [141]	N/A	M: Radio Absorption, Amplitude Attenuation; L: SVM	Humidity Estimation	Average Accuracy: 79%
UbiBreathe [1]	NR: Local Mean Removal, α-Trimmed Mean Filter; ST: FFT, DWT; SE: BPF, Thresholding	M: dominant periodic component due to inhaling and exhaling	Breathing Rate & Apnea Estimation	breath rate error: 1bpm; breath apnea accuracy: 96%
BodyScan [18]	ST: FFT; SE: Butterworth LPF, PCA, Thresholding	M: PSD, Statistical Distribution; L: SVM	Activity Recognition, Breathing Monitoring	Recognition Accuracy: 72.3% (5 activities), Breathing Rate Accuracy: 97.4%
Liu-2015 [56]	NR: Hampel Filter, MA; ST: FFT; SE: BPF, Subcarrier Selection by CSI Amplitude Variance, Thresholding	M: Radio Scattering, Fading, and PDP, k Means by PSD	Breathing & Heart Rate Estimation	Breathing Rate Error: <1.1bpm (1 person), <1.2bpm (2 persons); Heart Rate Error: <5bpm (1 person)
Wi-Sleep [57, 58]	NR: Hampel Filter, Wavelet Filter; ST: DWT; SE: Interpolation, Subcarrier Selection by Periodicity and SVD, Multiple TX-RX Pairs	M: CFR	Respiration Rate & Apnea Estimation; Posture Change Detection	Respiration Rate Estimation: 85%; Posture Change Detection: 83.3%; Apnea Estimation: 89.8%
Ma-2016 [61]	NR: Hampel Filter, MA	M: Fresnel Zone Model	Respiration Estimation	N/A
WiHealth [80]	NR: Median Filter, LPF; SE: BPF, Polynomial Filter, Thresholding	M: Multi-Path Fading, Small Scale Fading	Breathing & Heart Rate Estimation	Estimation Error: 0.6bpm (breathing rate), 6bpm (heart rate)
Wang-2016 [91]	NR: Hampel Filter, MA; SE: Subcarrier Selection, Thresholding, Signal Separation	M: Fresnel Zone Model, PSD	Breathing Rate Estimation	N/A
TinySense [95]	ST: IFFT; DWT; SE: Thresholding, Mean Filter, Wavelet Filter, Multiple TX-RX Pairs	M: Fresnel Zone Model, ToF	Multi-Person Breathing Estimation	Accuracy: >88% (2 persons)
PhaseBeat [100]	NR: Hampel Filter, PBD, SFO, CFO; ST: FFT, DWT; SE: Subcarrier Selection, Thresholding	M: CFR, Phase Difference, MUSIC	Breathing & Heart Rate Estimation	Estimation Error: <0.85bpm (breathing rate), <10bpm (heart rate)
TensorBeat [101]	NR: Hampel Filter, PBD, SFO, CFO; SE: Thresholding	M: Phase Difference; L: Canonical Polyadic Decomposition, DTW, Dynamic Programming	Multi-Person Breathing Estimation	Estimation Error: <0.9bpm/1.9bpm (1 person/5 persons)
Zhang-2018 [138]	N/A	M: Fresnel Zone Model, Radio Diffraction	Respiration Estimation	Estimation Accuracy: 61.5% to 98.8%
Domenico-2016 [15]	SE: Euclidean Distance	L: Linear Discriminant Classifier	Human Counting	Recognition Accuracy: 52% to 74% (7 persons)

(Continued)

Table 9 Continued

Reference	Signal Processing	Algorithm	Application	Performance
MAIS [20]	ST: Linear Transform; SE: LPF, Outlier Filter, Thresholding, Eigen Values	L: kNN	Human Counting, Activity Detection & Recognition	Anomaly Detection: 98.04%, Human Counting: 97.21%, Activity Recognition: 93.12%
FCC [119]	SE: Multiple RXs	M: Rician Fading, Grey Verhulst Model, Percentage of Zero Elements	Human Counting	Error: <3/5 persons (indoor/outdoor, 15 total persons)
Mohammad-moradi-2017 [65]	SE: Signal Compression by Averaging	M: Threshold-Based Hierarchy, Signal to Noise Ratio	Room Occupancy Estimation	Accuracy: 89% (up to 3 persons)
Guo-2017 [29]	NR: ; ST: FFT; SE: LPF, Subcarrier Selection	M: Phase Difference, CSI Variance, EMD, Total Harmonic Distortion	Human Dynamics Monitoring	Accuracy: >90% (number, density, speed, and direction)
Wang-2014 [104, 105]	NR: Dynamic Exponential Smoothing Filter; SE: Interpolation, Thresholding	L: Linear Regression, Feature-Driven Estimation, Bayesian Network, Directed Acyclic Graph	Human Queue Estimation	Estimation Error: <10 seconds (up to 180 seconds queue length)
Wision [35]	ST: FFT; SE: Interference Nulling, Multiple TXs	M: AoA, Diffuse/Specular Radio Reflections, Diffraction	WiFi Imaging	Median Localization Accuracy: 26cm (static human); 15cm (metallic objects)
Karanam-2017 [42]	N/A	M: Markov Random Field Modeling, Loopy Belief Propagation, Sparse Representation	WiFi Imaging	Distance Error: 1.35% to 3.7%
Ulysses [153]	NR: Majority Vote	M: Specular Reflection, AoA, AoD, Threshold-Based Detection	Object Recognition; WiFi Imaging	Top-3 Accuracy: 100% (11 objects); imaging error: <8cm/1 degree (width/orientation)
Zhu-2015 [154]	SE: Thresholding	M: AoA, Radio Reflection, Absorption & Scattering, Majority Vote	WiFi Imaging	Estimation Error: <4.5cm/1 degree (width/orientation)

Computation overhead is not a major issue for detection applications due to low input data volume and low complexity for the detection algorithms.

5.2 Recognition Applications

Table 8 shows the summary of WiFi sensing for multi-class classification tasks. Most of the recognition applications are on activity recognition, gesture recognition, and human/user identification and authentication. The number of classes of most recognition applications is about 10. Almost all the recognition applications use learning-based algorithms as the classifier. SVM is still one of the most used algorithms as the classifier. Recognition applications use multi-class SVM instead of one-class SVM for detection applications. Another two widely used classifiers are kNN and DTW. DTW is usually used for kNN as the distance metric. Among the 39 papers on activity and gesture recognition, 8 use SVM, 9 use kNN, and 12 use DTW as the classifier. SVM is the classifier of 6 papers among the 12 papers on human/user identification and authentication. There are several recognition applications using HMM or CNN as the classifier. Many recognition applications use hybrid algorithms which usually first extract information using modeling-based algorithms and then recognize the targets using learning-based algorithms.

Learning-based algorithms are usually not so sensitive to noises and outliers as modeling-based algorithms. Many recognition applications use no or very simple noise reduction methods such as averaging and median filter, instead of complex algorithms such as the Hampel filter and LOF. Noise reduction is used for hybrid algorithms wherein modeling-based algorithms could be sensitive to noises. SVM and kNN are instance-based learning algorithm which need to calculate the distance from the testing instance to all the training instances. This could introduce expensive overhead when there are multiple classes and each class instance has many CSI data points. Many recognition applications, especially those using SVM, kNN, and/or DTW as the classifier, usually employ feature extraction, subcarrier selection, or dimension reduction to reduce the input size.

5.3 Estimation Applications

The summary of WiFi-based estimation applications is presented in Table 9. For estimation applications, most papers are on human/object localization and tracking. There are also many papers on the estimation of breathing rate, heart rate, and human counts. There are four papers using WiFi for wireless imaging. Different from detection/recognition applications aiming for binary/multi-class classification problems, estimation applications try to calculate the quantity values of size, length, angle, distance, duration, etc. Almost all the estimation applications use modeling-based algorithms, such as AoA, ToF, Fresnel Zone Model, Doppler Spread, MUSIC, etc. For all the 19 papers on human/object localization and tracking, 5 use AoA, 6 use Doppler/Phase Shift, 3 use Fresnel Zone Model. Among 12 papers on breathing/heart rate estimation, 4 use Fresnel Zone Model. Only 6 papers of estimation applications, including 1 on human localization [148], 1 on vehicle speed estimation [111], and 4 on human counting [15, 20, 104, 105], employ only the learning-based algorithms but no modeling-based algorithms. Since modeling-based algorithms are sensitive to noises, estimation applications usually require many efforts on removing noises, especially phase offsets. Many estimation applications employ signal composition techniques, e.g., multiple WiFi devices, frequency bands and data packets, to improve the estimation accuracy.

6 CHALLENGES AND FUTURE TRENDS OF WIFI SENSING

Existing WiFi sensing mostly focuses on humans. Future WiFi sensing could be in other domains, such as detecting, recognizing, and estimating the surrounding environments, animals, and objects. This section presents the challenges and future trends for both existing and future WiFi sensing. New opportunities for signal processing techniques and algorithms of WiFi sensing are also presented.

6.1 WiFi Sensing Challenges

6.1.1 Robustness and Generalization. WiFi signals are very sensitive to many different factors such as network settings, environments, objects, humans, geometry and mobility situations, etc. It is crucial and also challenging for WiFi sensing to be robust in different real-world scenarios and settings. For example, the distance between the person and the WiFi transmitter/receiver could be different. The direction and orientation of the person with respect to the WiFi transmitter/receiver could also change. There could be multiple persons or other moving objects around. The person or other objects could block the direct path between the transmitter and receiver. It is more challenging for WiFi sensing algorithms, both modeling-based and learning-based, to have the generalization ability of properly and automatically adapting to new and previously unseen data. For example, WiFi-based activity recognition should also work when WiFi devices are placed in a new environment at unknown locations/orientations and for new persons whose data are not seen before. Learning-based algorithms also have under-fitting issues when there are not enough training data. To guarantee the robustness and generalization of WiFi sensing, it requires effective and efficient ways to find the right data collection methods, signal processing techniques, theoretical/statistical models, and machine learning algorithms.

6.1.2 Privacy and Security. One of the advantages of WiFi sensing is that it is non-intrusive and non-obtrusive. But this introduces many privacy and security issues. As shown in Section 5, there are already many WiFi sensing applications that can infer both coarse-grained and fine-grained information such as daily activities, gestures, and keystrokes. These information can be easily leaked to malicious hackers and attackers. Moreover, the victim user may be unaware of the information leakage since it is non-obtrusive and WiFi signals can travel through walls. Unlike images and videos, WiFi signals are not limited to lighting conditions, so WiFi sensing is very easy to be used for malicious purposes. This could be in conflict with the purpose of robustness and generalization of WiFi sensing: the former one needs to make it harder to leak information while the latter requires more information to be easily inferred in different scenarios. Therefore, new protocols, policies, architectures, and algorithms are needed for the privacy and security of WiFi sensing.

6.1.3 Coexistence of WiFi Sensing and Networking. WiFi is designed for wireless communications but not for sensing applications. When a WiFi device is used for sensing, it could influence the network performance and also be impacted by network settings. Some WiFi sensing applications require high CSI measurement frequency to get high performance results. This could introduce overhead for WiFi communications and result in reduced network performance and efficiency. Moreover, sending unnecessary CSI measurement packets influences not only the measurement device but also other nearby WiFi devices, since it occupies WiFi resources and influences the scheduling process in the time and spectrum domains. On the other hand, WiFi sensing is impacted by WiFi network settings. For example, WiFi transmitters may use beamforming which changes the amplitude and phase of CSI measurements, as shown in equation (2). This completely changes CSI patterns and is very hard to process if the beamforming matrix is not available at the receiver.

6.2 Future WiFi Sensing Trends

This section presents future WiFi sensing trends for addressing the above-mentioned challenges for both existing and future WiFi sensing, as shown in Fig. 9.

6.2.1 Cross-Layer WiFi Sensing. This survey only focuses on WiFi sensing with the physical layer information, i.e., CSI. CSI can be integrated with upper layer information for cross-layer WiFi sensing. This could help develop new sensing applications or enhance existing WiFi sensing applications. Upper layer WiFi information, such as Medium Access Control (MAC), Transmission Control Protocol (TCP), and Internet Protocol (IP), can also be used for sensing purposes. For example, MAC and IP packet headers from WiFi probing requests can be used to predict smartphone screen on/off [37], human flow [9, 71, 144, 145], urban mobility [13], and social relationship [9, 45]. Combining CSI with MAC and IP layer information could help enhance the capability of WiFi sensing. Cross-layer WiFi sensing provides additional information from other domains, which can improve the robustness and generalization of WiFi sensing. Cross-layer WiFi sensing can also be used for improving security and privacy. There are already many papers on CSI-based user identification/authentication [10, 11, 34, 53, 54, 82, 96, 97, 118, 124, 133, 139] and other security and privacy purposes [8, 50, 125]. These applications can be improved by incorporating CSI with upper layers such as Transport Layer Security (TLS), Secure Sockets Layer (SSL), application layer, and user interface. Upper WiFi layers can also be re-designed to guarantee WiFi sensing is not misused for malicious purposes. Finally, cross-layer WiFi information can help WiFi sensing and networking be aware of each, so it helps address the coexistence of WiFi sensing and networking.

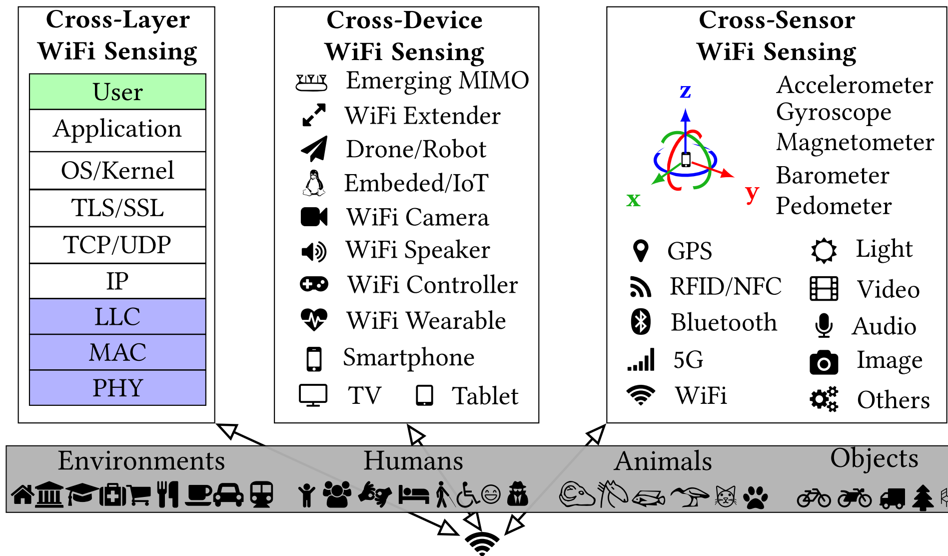


Fig. 9. Future trends of WiFi sensing. CSI from WiFi can be used to sense the surrounding environments, humans, animals, and objects using cross-layer information, multiple devices, and fusion of different sensors.

6.2.2 Cross-Device WiFi Sensing. Some WiFi-based localization and tracking applications use CSIs from multiple WiFi devices. Other WiFi sensing applications can also combine multi-device CSIs for higher performance and efficiency. In addition to WiFi APs, many other WiFi-enabled devices, e.g., cameras, speakers, drones, robots, Internet of Things (IoT) devices, etc., can be used. Due to the rapid development and high demand of wireless data, there will be more WiFi devices in different scenarios, such as home, office, school, outdoor, stadium, shopping malls, etc. These WiFi devices have time and location dependence which could provide more information for WiFi sensing. Moreover, CSI measurements can be collected by emerging MIMO technologies such as distributed, cooperative, massive, 3D, and full dimension MIMO [155]. Current WiFi sensing applications only use CSIs measured by traditional MIMO systems. CSIs of emerging MIMO technologies could open new opportunities for WiFi sensing in terms of signal processing techniques, channel models, learning algorithms, application types. Platforms for measuring CSIs of these emerging MIMO technologies are also needed for WiFi sensing purposes. Cross-device WiFi sensing provides more information in different domains, e.g., time, space, frequency, user, etc. It also gives cross-correlation and dependence information among multiple devices. The cross-device information is useful for improving the robustness and generalization of WiFi sensing.

6.2.3 Cross-Sensor WiFi Sensing. Some sensing applications use the fusion of CSIs with other signals, such as videos and audios, as the input [10, 38, 65]. CSIs can be combined with other sensor sources, e.g., Bluetooth, 5G, ZigBee, GPS, microphones, image/video cameras, motion sensors, etc., for cross-sensor WiFi sensing. For example, video cameras and CSIs can be combined together for higher performance and less human efforts of training machine learning algorithms. When the light condition is good, video cameras can be used for ground truth labeling for the machine learning algorithms that use CSIs as the input. The CSI-based learning algorithms can be activated when video cameras are not reliable due to poor light conditions. The fusion of video cameras and CSIs can provide a better time coverage than they are used separately. Moreover, the human efforts of data collection, ground truth labeling, and model training can be significantly reduced. There are many pre-trained neural networks that use videos as the input. These video-based neural networks can provide near human-level performance which can be used to automatically label CSI measurements. This could save a lot of time and computation resources for training the machine learning algorithms. The fusion of WiFi and other sensors also helps improve the robustness and generalization of WiFi sensing by integrating information from other domains.

All these WiFi sensing trends can be integrated to provide multi-domain knowledge. For example, wireless drones and robots have the whole WiFi network stack, multiple cooperative devices, and different sensors. They can combine cross-layer network information, multi-device cooperation, and fusion of different sensors for more effective WiFi sensing.

6.3 Future Opportunities for Signal Processing and Algorithms of WiFi Sensing

Future WiFi sensing trends also bring new opportunities and challenges for signal processing techniques and classification/estimation algorithms. Existing noise reduction techniques mostly focus on removing noises, interferences, and unintended signals for a single device. New noise reduction techniques and hardware designs are needed to deal with noise signals from multiple devices and other domains. Since there are multi-domain signals from upper network layers, multiple devices, and sensor fusions, new signal compression techniques are needed to remove redundant and unrelated components for more efficient processing. Existing signal composition techniques of WiFi sensing are mostly for combining only CSI from multiple devices. New schemes are needed to integrate CSI with signals and information from other domains. It is also important to balance signal compression and composition for efficient and effective WiFi sensing.

New WiFi sensing algorithms are also required to take full advantage of multi-domain information with time, spatial, and user dependence. New coordination algorithms are necessary for extracting useful information from different domains. Since CSI has some unique properties such as low spatial resolution and sensitive to environmental changes, it is crucial for WiFi sensing algorithms to be robust in different scenarios. Most existing deep learning solutions of WiFi sensing reuse DNNs for images and videos. It is necessary to find suitable DNN types and develop new DNNs specifically designed for CSI data. For cross-sensor WiFi sensing, pre-trained DNNs for other sensors can be used for automatic labeling of CSI data. Transfer learning, teacher-student network training, and reinforcement learning can also be used to reduce network training efforts. WiFi sensing is very easy to be used for malicious purposes, since WiFi signals can be passively transmitted through walls and are not limited to lighting conditions. Generative Adversarial Networks (GANs) [25, 26] can be used to generate fake WiFi signal patterns to prevent from malicious WiFi sensing.

7 CONCLUSION

This paper gives a survey of signal processing techniques, algorithms, applications, and performance results of WiFi sensing with CSI. It presents the basic concepts, advantages, limitations and use cases of the signal processing techniques and algorithms for different WiFi sensing applications. The survey highlights three WiFi sensing challenges: robustness and generalization, privacy and security, and coexistence of WiFi sensing and networking. Finally, the survey presents three future trends: integrating cross-layer network stack, multi-device cooperation, and fusion of different sensors, for improving existing WiFi sensing applications and enabling new sensing opportunities.

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