Device-Free Wireless Sensing: Challenges, Opportunities, and Applications

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Abstract

Recent developments on DFWS have shown that wireless signals can be utilized not only as a communication medium to transmit data, but also as an enabling tool for realizing non-intrusive device-free sensing. DFWS has many potential applications, for example, human detection and localization, human activity and gesture recognition, surveillance, elder or patient monitoring, emergency rescue, and so on. With the development and maturity of DFWS, we believe it will eventually empower traditional wireless networks with the augmented ability to sense the surrounding environment, and evolve wireless communication networks into intelligent sensing networks that could sense human-scale context information within the deployment area of the network. The research field of DFWS has emerged quickly recently. This article tries to provide an integrated picture of this emerging field and hopefully inspire future research. Specifically, we present the working principle and system architecture of the DFWS system, review its potential applications, and discuss research challenges and opportunities.

Introduction

Device-free wireless sensing (DFWS) [1, 2] is an emerging technique that could estimate the presence, location, motion, activity, and gestures of a person without equipping him/her with any device. Wireless signals are widely recognized as the most successful medium to realize communication. No matter where we are, there are nearly inevitable wireless signals around us, for example, WiFi, 3G/4G, FM, TV, and so on. A person within the deployment area of the wireless network influences wireless signals in a predictable way, which renders it feasible to sense the human state by analyzing the wireless signal patterns and characteristics. Compared with other state-of-the-art sensing techniques, such as cameras and wearable sensors, DFWS does not require specially deployed sensing devices, can work well under smoky or dark conditions, and does not result in privacy leaks. The aforementioned advantages make DFWS an ideal technique for pervasive sensing applications. Furthermore, DFWS enables traditional wireless networks with the augmented ability to sense the surrounding environment. It may eventually evolve wireless networks into intelligent sensing networks that could sense human-scale context information within the deployment area of the network.

The research field of DFWS has emerged and developed quickly recently. Researchers have utilized different intrinsic parameters, for example, received signal strength (RSS) [3–9] time-of-flight (TOF) [10], and channel state information (CSI) [11–15], of wireless signals to realize device-free localization [3, 5–7, 10, 12], activity recognition [4, 8, 9, 11, 13], respiration detection [14], and gait recognition [15]. They have explored the model-based approach [5–7, 10, 14] and the machine learning approach [4, 8, 9, 11, 13, 15] to establish the association between intrinsic signal parameters and the human state to be estimated. The above work effectively promotes the development of the DFWS technique. However, due to the significant difference between different intrinsic parameters, different approaches, and different applications, the field of DFWS is somewhat fragmented. This article tries to provide an integrated picture of this emerging field by presenting the working principle and system architecture of the DFWS system, reviewing its potential applications, and discussing research challenges and opportunities.

This article is structured as follows. We introduce the working principle of the DFWS system and present its system architecture. We review potential applications that exploit DFWS technique. We discuss existing research challenges and forecast opportunities for future research.

Working Principle and System Architecture

Working Principle

Essentially, the DFWS technique leverages shadowing, diffraction, reflection, and scattering phenomena exerted by a person on wireless links to estimate the human state. When a person stands within the effective area of a wireless network, they will unavoidably disturb the propagation of wireless signals. Figure 1 illustrates the visualized amplitude and phase measurement acquired when a target stands at two different locations and performs two different activities (swing arms and wave hands). From the figure, we can see that the influence of the target is different for different locations or activities. Researchers have discovered that the influence of a person on wireless signals is repeatable and predictable, which makes it feasible to sense human state by analyzing the wireless signal patterns and characteristics.

How to build a model to characterize the influence of a person on wireless signals is the key issue of DFWS. However, the propagation characteristics of wireless signals are extremely complex. Thus it is challenging to develop a perfect mathematical model. Existing models can be roughly classified into the following categories.

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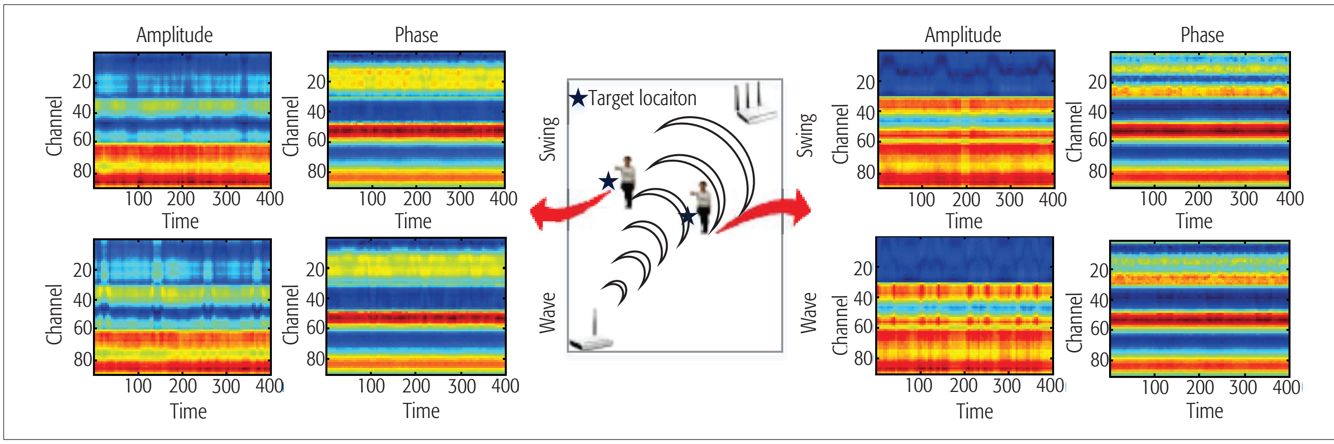

FIGURE 1. Working principle of DFWS system.

Binary Model [3]: It uses a threshold value to determine whether a wireless link is shadowed by a person or not. Generally, if a link is shadowed, the signal amplitude will reduce, the TOF will increase, and the variances of amplitude, phase, and TOF will increase. Therefore, based on these statistical parameters, it is not difficult to detect the shadowed links. The binary model supposes that the person must stand close to the shadowed links, for example, it always adopts a rectangular area around the shadowed link to characterize the feasible positions of the person. Compared with other models, the computational complexity of the binary model is low. However, it could only provide binary information about whether a person is close enough to a wireless link.

Elliptical Model [5, 10]: It supposes that the effective area of a person should be an elliptical area. Meanwhile, it supposes that the closer a person is to the wireless link, their influence on the link will be larger. As a result, the change of RSS, TOF, and CSI will be more significant. The elliptical model not only gives binary information similar to the binary model, but also provides the degree of closeness to the wireless link.

Saddle Surface Model [7]: By taking the distances to the transceivers into consideration, the saddle surface model could provide more detailed information within the elliptical area. Compared with the elliptical model, it could also provide the degree of closeness to the transceivers.

Diffraction Model [6]: Compared with other models, it looks on a person as a columnar object instead of a point object, and characterizes the influence of the person using knife-edge diffraction theory. The diffraction model could deal with the cases that a person moves along, across, or away from the line of sight (LOS) path.

Fresnel Zone Model [14]: It describes the multipath propagation in free space using a series of ellipsoids with foci in the pair of transceivers. When a person moves within the Fresnel zones, the reflected path will combine with the LOS path, which results in constructive and destructive interference as the reflected path goes in and out of phase with the LOS path. Therefore, the Fresnel zone model can characterize the movement speed of a person based on the change rate of the signal amplitude.

Machine Learning Approach [4, 8, 9, 13, 15]: Since the influence of a person on wireless signals is too complex, researchers have also explored characterizing the influence using the data-driven approach. They adopt machine learning methods to learn the complex relationship between signal parameters and human state, and establish their association accordingly. Although machine learning methods cannot give an analytical expression of the relationship, they indeed could well establish the association.

System Architecture

The architecture of a DFWS system is illustrated in Fig. 2. The system is mainly composed of three functional modules: the signal acquisition and pre-processing module, the signal feature extraction module, and the human state estimation module. Detailed information about each module follows.

Signal Acquisition and Pre-Processing: DFWS systems generally utilize networked measurement information or single link measurement information to acquire intrinsic parameters, for example, RSS, phase, AOA, TOF, and CSI, of wireless signals. While single link measurement information is sufficient for estimating simple human state near the link, networked measurement information empowers the DFWS system with the ability to sense the whole deployment area of the network. The characteristics of the intrinsic parameters are as follows.

RSS: RSS is a basic parameter provided by almost all kinds of transceivers. Mainstream wireless technology, such as WiFi, Zigbee, GSM/3G/4G, Bluetooth, FM, and TV, could provide RSS information directly. The advantage of RSS is that it is easy to get, and the disadvantage is that RSS is too noisy.

Phase: Compared with RSS, phase parameter is more sensitive to human influence. Thus, it can be utilized to recognize human activities. Phase parameter is relatively easy to get, while it is meaningful only when the transmitter and receiver are synchronized.

TOF: TOF parameter is robust to environmental noise. It could provide robust measurement information for DFWS systems. However, similar to phase parameters, it also requires the synchronization between the transmitter and receiver. Two-way ranging defined by 802.15.4a is a new scheme to measure TOF without the need for synchronization. It eliminates the non-synchronous error with the cost of performing bidirectional distance measurement for multiple times.

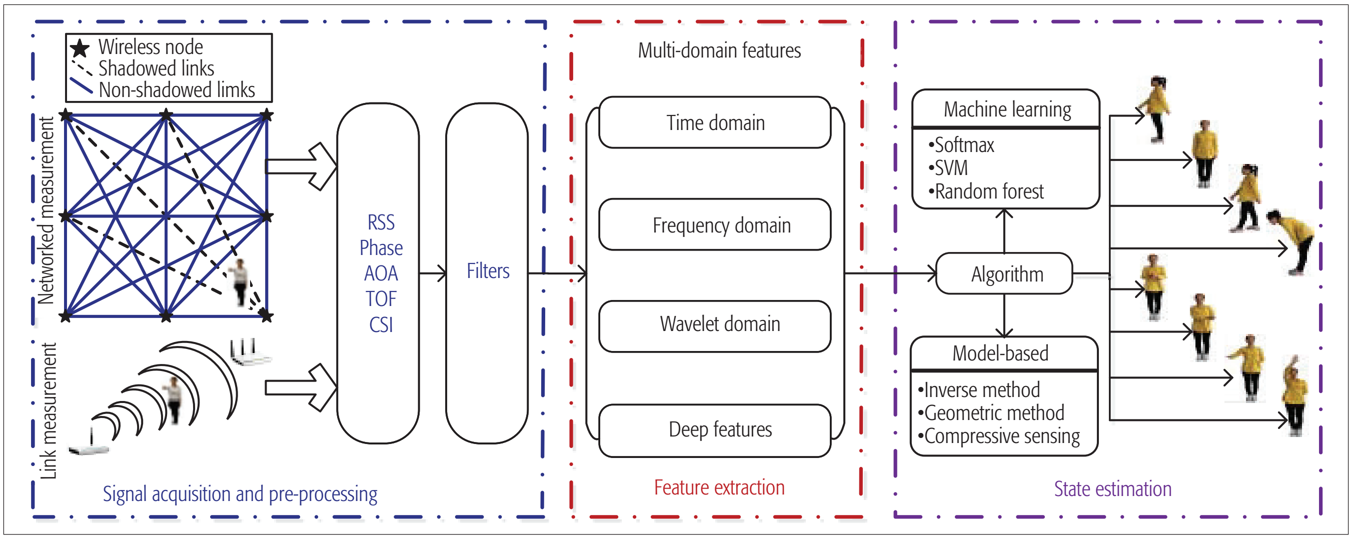

FIGURE 2. System architecture of DFWS system.

CSI: CSI essentially can be seen as the RSS and phase information on multiple channels, thus, it could provide a wealth of information and makes it possible to recognize small-scale human gestures. CSI information can be measured if the wireless communication system utilizes orthogonal frequency division multiplexing as the modulation method. Fortunately, most advanced transceivers, such as WiFi, could provide CSI information. The advantage of CSI is that it could provide informative amplitude and phase information on multiple channels.

AOA: With the popularity of the multiple input multiple output technique, more and more wireless devices are equipped with multiple antennas, which renders it feasible to estimate the AOA parameter. Compared with the aforementioned parameters, AOA could characterize the signal from the space perspective, which can enlarge the diversity of the measurement. With the advances in communication technology, state-of-the-art transceivers can provide most of the parameter information described above.

Since raw measurement information is too noisy, many pre-processing schemes have been utilized to improve signal quality. For example, bandpass filters are used to eliminate out-of-band interference, smoothing filters are utilized to smooth the signal, and principal component analysis method is adopted to extract the principle signal from the measurement.

Feature Extraction: The goal of the feature extraction module is to extract discriminative and representative features from the denoised signals. Generally adopted features can be classified as time-domain features, frequency-domain features, wavelet-domain features, and deep features. To sense simple human state such as location information, simple time-domain statistical parameters, for example, mean or variance, are sufficient. However, if we want to sense human activities, we have to extract more informative features, for example, high-order statistics or distribution. With the reduction of the scale of human actions, the DFWS problem becomes more challenging. The features extracted from only time-domain can no longer meet the requirement. We have to utilize the features extracted from multiple domains, for example, frequency domain and wavelet domain, to build multi-domain features. More recently, inspired by its excellent feature extraction ability, deep learning networks have also been utilized to extract deep features from the denoised signals. Several commonly used features are as follows.

Time-Domain Features: Extracted directly from the time-domain denoised signals. Some commonly used features are: mean, variance, peak-to-peak value, high-order statistics, and distribution.

Frequency-Domain Features: Using Fourier transformation, we can transform the signals from time-domain into frequency-domain. Then, some statistical features, for example, energy, entropy, peak frequency, and spectrum distribution, can be utilized to characterize the frequency-domain signals.

Wavelet-Domain Features: As a multi-scale time-frequency analysis tool, wavelet transformation can transform time-domain signals into multiple frequency bands with different time resolutions. Then, we can extract statistical features from each band, and form the multi-scale time-frequency domain features.

Deep Features: Deep learning networks, such as sparse auto-encoder networks and convolutional neural networks, can extract deep features from the denoised signals. Compared with other features, deep features can be extracted automatically. Furthermore, it has better discriminative and representative ability with a high probability.

Human State Estimation: With signal feature information, we can estimate human state using many algorithms. The algorithms can be roughly divided into two categories: model-based and machine-learning based.

Model-Based Approach: If there is a model that could characterize the influence of a person on wireless signals, we can build the relationship between human state and the observed signal features, and thus formulate the DFWS problem and solve it accordingly. Researchers have successfully formulated the device-free localization question as a matrix inversion problem and solved it with regularization methods [11]; as a spatial intersection problem and solved it with geomet-

FIGURE 3. Research challenges and opportunities.

ric methods [10]; and as a sparse representation problem and solved it with compressive sensing methods [13]. The advantage of the model-based approach is that it does not need the time-consuming training procedure. Meanwhile, its computational complexity is relatively low. However, it is generally challenging or even impossible to build an accurate model to characterize the influence of a person. Although researchers have built some models for associating the location of a person with different signal features, there is still a lack of effective models to characterize complex human state.

Machine-Learning Approach: As a successful data-driven analysis tool, machine-learning methods have the ability to learn, discover, and build complex relationships between multiple factors. As described above, human state, such as activity and gesture, exerts complex influence on wireless signals, making it difficult or even impossible to characterize their influence using models. Therefore, researchers have tried to utilize machine-learning methods to model DFWS as a multi-class classification problem, and solved it with the softmax regression method [16], support vector machine [15], and random forest method. Generally speaking, machine-learning methods are composed of the following two phases: off-line training phase and on-line classification phase. In the off-line training phase, using the labeled training data, i.e., the signal features and the corresponding human state, we can train the machine-learning network and determine the parameters of the network. In the on-line classification phase, with the extracted signal features as the network input, the machine-learning network could output the probabilities of each human state. The advantage of the machine-learning approach is that it is suitable for complex human state estimation, as long as the influence of different human states is different. The disadvantage is that it needs off-line training which is time consuming and labor intensive.

Potential Applications

Context information provided by the DFWS technique will provide great opportunities for new services. Potential applications can be roughly divided into the following two categories. One is analyzing the pattern of the human state so as to help public services such as security monitoring and emergency rescue. The other is analyzing the state of a person so as to provide personal services such as intelligent interaction and intelligent monitoring. In essence, the DFWS technique could provide a huge amount of data about the human state. Based on these data, big data analysis methods can be utilized to mine the useful information inherent to the data.

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One advantage of DFWS based applications is that they can realize the sensing task by upgrading the firmware and protocol of traditional wireless networks, which eliminates the need to deploy new hardware. Another advantage is that they can sense almost anywhere, which benefits from the ubiquity of wireless signals. Some typical applications of the DFWS technique (Fig. 3) are as follows.

Security Monitoring: There are many applications that aim to monitor the occurrence of abnormal events, i.e., a border monitoring system monitors whether anything crosses the border, a bank monitoring system monitors whether there is any motion in the evening, and so on. Owing to its ability to provide a large coverage area and work well in smoky or dark conditions, DFWS is an ideal technique for these applications.

Emergency Rescue: If there is a need for fire rescue and hostage rescue, we want to get information about the human state in the building before performing the rescue operation. The DFWS technique can well address this issue. It could provide not only the location information of persons in the building, but also their motion and activity information as well. This information effectively reduces the blindness of the rescue action, and enhances the safety of the relevant personnel.

Intelligent Interaction: In science fiction movies, people in the future always interact with computers through gestures, which are attractive and mysterious. The DFWS technique will turn these scenarios into reality. Nowadays, almost every urban space is covered by WiFi or other wireless signals. The DFWS technique senses the location, activity, and gestures of persons by analyzing the

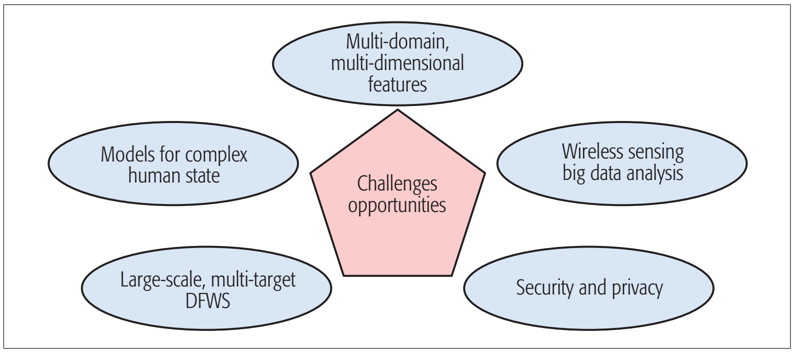

FIGURE 4. Applications of DFWS technique.

surrounding wireless signals, and performs proper operations accordingly. With the maturity of the DFWS based intelligent interactive applications, smart houses and smart buildings will appear and our living environment will become more intelligent.

Intelligent Monitoring: The problem of population aging has become increasingly prominent. How to monitor the elderly without privacy disclosure and without interfering in their daily life becomes an urgent problem solve. DFWS is a suitable candidate technique that meets all of the above requirements. A state-of-the-art DFWS technique can not only estimate location and activity information, but also estimate the respiratory rate and detect the occurrence of falls, which are important for elderly monitoring. Similarly, other intelligent monitoring scenarios, such as a chronic patient monitoring system and baby care system, can benefit from the DFWS technique as well.

Research Challenges and Opportunities

Although the DFWS technique has made great progress recently, there are still many problems to be solved, as summarized in Fig. 4. The detailed information of the problems is as follows.

Models for Complex Human State

Researchers have proposed many models to characterize the influence of a person on wireless signals. However, most models can only characterize the relationship between simple human state, such as different locations of a person, and simple signal features, such as mean and variance of the signals. It is still a challenging problem to model the influence of complex human state. Generally, complex human state can be decomposed into a series of simple actions, and simple actions usually can be characterized by action features such as action amplitude, action speed, and action duration. If we can build the relationship between signal features and action amplitude, action speed, and action duration, it will become feasible to decompose the complex human state model into multiple relatively simpler models, i.e., the action amplitude model, action speed model, and action duration model. Then, we can build the mathematical formulation for these simpler models, and utilize these simpler models jointly to characterize the complex human state. With the aforementioned strategy, we can decompose a complex human state model into multiple simpler models, so as to achieve the goal of characterizing the influence of complex human state.

Multi-Domain Multi-Dimensional Signal Feature Extraction

Signal features are the key factors for characterizing the influence of the human state on wireless links. A simple feature can only characterize the influence from a limited perspective, while an informative feature can provide more detailed information. Although researchers have explored and exploited numerous features to characterize the raw wireless signal, there is still much room for improvement. For example, most currently utilized features are extracted from only time domain and frequency domain, and from only a limited number of antennas, which could characterize signal features only from a limited perspective. With the continuous growth of computational capability, it becomes feasible to utilize a more professional transformation domain signal analysis technique, such as Hilbert transformation, to extract signal features from multi-domain. Meanwhile, with the popularity of massive multiple input multiple output systems, it becomes possible to acquire and deal with signals using multiple antennas, so as to observe and analyze human state from a multi-dimensional perspective. It is foreseeable that future DFWS techniques must utilize signal features extracted from multi-domain and multi-dimensional perspectives.

Large-Scale Multi-Target Scenario

Currently, limited by models and algorithms, the state-of-the-art DFWS system can estimate the state of a very limited number of or even only one person. To achieve the ambitious goal of evolving wireless networks into intelligent sensing networks that could sense human-scale context information within the deployment area of the network, we must enable DFWS systems with the ability to sense multiple targets simultaneously. However, the shadowing effects of multiple targets intertwine with each other, which makes it challenging to realize multi-target sensing. Furthermore, the deployment area of the DFWS system is generally in the scale of hundreds of square meters, which cannot meet the ambitious goal, either. Therefore, developing new DFWS techniques suitable for the large-scale multi-target scenario becomes a rigid demand. For the large-scale scenario, we must develop new techniques to divide the large-scale deployment area into multiple sub-areas and realize human state estimation in every sub-area simultaneously. For the multi-target scenario, we must design new methods to estimate the number of persons, isolate the influence of each person, and estimate the state of each person.

Wireless Sensing Big Data Analysis

With progress and maturity of the DFWS technique, it will provide network operators with an enormous opportunity to collect a huge amount of data about human state information within the deployment area of wireless networks. This context information meets the 4V characteristics, i.e., volume, variety, velocity, and value, of big data. Using these data, we can monitor crowd distribution information, analyze the living habits of a person, build smart buildings, and so on. However, there is still a lack of ways to effectively use these data. The research on this issue is still an under-exploited gold mine.

Security and Privacy

Human state information is always privacy-sensitive. Therefore, how to preserve privacy while realizing DFWS will pose great challenges. On one hand, we may utilize data encryption and user authentication techniques to ensure the privacy of users. On the other hand, we can use physical layer security methods to further enhance the security of human state information.

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Conclusion

In this article, we present the working principle of the DFWS system, introduce its system architecture, and discuss detailed signal acquisition and pre-processing methods, feature extraction schemes, and human state estimation algorithms. Based on these, we review potential applications, and analyze and discuss the main challenges and opportunities for future research. The main purpose of this article is to provide a comprehensive overview of this emerging field and hopefully to motivate researchers and engineers to move forward with more creative designs on DFWS.

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References

[1] Z. Zhou *et al.*, "Sensorless Sensing with WiFi," *Tsinghua Science and Technology*, vol. 20, no. 1, Jan. 2015, pp. 1–6.

[2] S. Savazzi *et al.*, "Device-Free Radio Vision for Assisted Living: Leveraging Wireless Channel Quality Information for Human Sensing," *IEEE Signal Processing Mag.*, vol. 33, no. 2, Mar. 2016, pp. 45–58.

[3] D. Zhang *et al.*, "Fine-Grained Localization for Multiple Transceiver-Free Objects by Using RF-Based Technologies," *IEEE Trans. Parallel Distributed Systems*, vol. 25, no. 6, June 2014, pp. 1464–75.

[4] J. Wang *et al.*, "Device-Free Wireless Localization and Activity Recognition: A Deep Learning Approach," *IEEE Trans. Vehicular Technol.*, vol. 66, no. 7, July 2017, pp. 6258–67.

[5] Y. Zhao and N. Patwari, "Robust Estimators for Variance-Based Device-Free Localization and Tracking," *IEEE Trans. Mobile Computing*, vol. 14, no. 10, Oct. 2015, pp. 2116–29.

[6] Z. Wang *et al.*, "A Diffraction Measurement Model and Particle Filter Tracking Method for RSS-Based DFL," *IEEE JSAC*, vol. 33, no. 11, Nov. 2015, pp. 2391–2403.

[7] J. Wang *et al.*, "Towards Accurate Device-Free Wireless Localization with a Saddle Surface Model," *IEEE Trans. Vehicular Technology*, vol. 65, no. 8, Aug. 2016, pp. 6665–77.

[8] S. Sigg *et al.*, "RF-Sensing of Activities from Non-Cooperative Subjects in Device-Free Recognition Systems Using Ambient and Local Signals," *IEEE Trans. Mobile Comput.*, vol. 13, no. 4, Apr. 2014, pp. 907–20.

[9] J. Wang *et al.*, "Device-Free Simultaneous Wireless Localization and Activity Recognition with Wavelet Feature," *IEEE Trans. Vehicular Technology*, vol. 66, no. 2, Feb. 2017, pp. 1659–69.

[10] J. Wang *et al.*,"Time-of-Flight-Based Radio Tomography for Device Free Localization," *IEEE Trans. Wireless Commun.*, vol. 12, no. 5, May 2013, pp. 2355–65.

[11] W. Wang *et al.*, "Device-free Human Activity Recognition Using Commercial WiFi Devices," *IEEE JSAC*, vol. 35, no. 5, May 2017, pp. 1118–31.

[12] Z. Yang, Z. Zhou, and Y. Liu, "From RSSI to CSI: Indoor Localization via Channel Response," *ACM Computing Surveys*, vol. 46, no. 2, Nov. 2013, pp. 1–25.

[13] Y. Wang *et al.*, "E-Eyes: Device-Free Location-Oriented Activity Identification Using Fine-Grained WiFi Signatures," *Proc. 20th Int'l. Conf. Mobile Computing and Networking*, Hawaii, USA, Sept. 7–11, 2014, pp. 617–28.

[14] H. Wang *et al.*, "Human Respiration Detection with Commodity WiFi Devices: Do User Location and Body Orientation Matter?" *Proc. ACM Int. Joint Conf. Pervasive and Ubiquitous Computing,* Heidelberg, Germany, Sep. 12–16, 2016, pp. 25–36.

[15] W. Wang, A. X. Liu, and M. Shahzad, "Gait Recognition Using WiFi Signals," *Proc. ACM Int'l. Joint Conf. Pervasive and Ubiquitous Computing*, Heidelberg, Germany, Sep. 12–16, 2016, pp. 363–73.

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