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Probing and deploying key wireless sensing technologies in the realm of 6G

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Abstract. In an effort to implement seamless, precise, and real-time wireless sensing within indoor environments, this paper delves into the principles and applications of sensing technology grounded in indoor wireless signals. The cornerstone of this study is the comprehensive understanding of wireless signal sensing which is intrinsically composed of four major stages. Initially, signal acquisition occurs, serving as the foundation for the entire process. Subsequently, data pre-processing refines these signals, ensuring the relevance and accuracy of the information for the upcoming stages. Thereafter, the methodical process of feature extraction takes place, which provides a nuanced understanding of the signal's key characteristics. This is vital in offering clear insights into the signal's inherent traits and potential implications. Finally, classification and identification occur. This stage sorts and labels the signals based on their unique attributes, allowing for an organized and efficient analysis. Furthermore, this paper extends to analyzing three distinct application scenarios that utilize this intelligent sensing technology. The first one entails behavior recognition, which could be instrumental in understanding and predicting human activity patterns within a specific space. Another application is in passive location identification, offering a non-intrusive means to track movements and locations within an indoor setting. By investigating these applications, we aim to provide a broad understanding of the potential of indoor wireless signal-based sensing technology, and to further its development and refinement for more diverse and efficient uses.

Keywords: wireless signals, channel state information, received signal strength indicator, frequency modulated continuous wave.

1. Introduction

As the Internet of Things (IoT) technology continues to advance, our living and working environments have become filled with a plethora of wireless signals, ranging from WiFi and Bluetooth to ZigBee, 4G/5G/6G, LoRa, and RFID. Wireless sensing typically leverages these ubiquitous wireless signals, used predominantly for daily communication, to perceive both individuals and the environment surrounding them. The ability to detect a communication signal arises from the multipath overlap of signals, produced when the radio waves generated by the signal transmitter undergo reflection, scattering, and refraction as they traverse through space [1]. These overlapping signals carry invaluable information that embodies the environmental characteristics where the signal receiver is located. From the standpoint of indoor wireless signals, this paper elaborates on the principles and processes of perception technology rooted in these signals. With a keen focus on the theoretical underpinnings and the practical procedures that define this technology, the discussion provides an exhaustive comprehension of its functioning.

2. Fundamentals of wireless signal sensing

The basic principle of wireless signal intelligent sensing is that the wireless signal transmitted by the transmitting end is superimposed at the receiving end through the direct path or the wireless signal through multiple paths such as reflection, refraction and diffraction with the human body through the surrounding environment. When the human body moves in the space of wireless signal transmission, the equipment uses effective signal feature extraction technology and artificial intelligence algorithm to process the wireless signal at the receiving end, So as to realize the perception of human activity state in the indoor environment. The general artificial intelligence algorithm model inputs channel state information, received signal strength indication and FM continuous wave intermediate frequency signal, also known as fwcw-if, which can be used in various sensing scenarios [2].

2.1. Channel state information (CSI)

CSI is a very important and practical data to describe the channel in wireless communication. In wireless communication, the channel state information represents the propagation characteristics of the communication link, which describes the joint influence of scattering, fading, power attenuation and other effects in the channel. The communication channel model is shown in formula (1).

$$Y = HX + N \tag{1}$$

In formula (1), Y is the signal vector at the receiving end, X is the signal vector at the transmitting end, h is the channel state matrix, and N is noise. The CSI can be represented by a matrix H, which is a collection of channel information of each subcarrier. Wherein, each Hk represents the amplitude and phase of a subcarrier. H appears in plural form. By obtaining the modulus and argument of the complex number, the corresponding amplitude and phase can be obtained [3].

2.2. Received signal strength indicator (RSSI)

RSSI represents the strength of the received signal and is expressed by formula (2):

$$R = 10lgP \tag{2}$$

In formula (2), P is the received signal power value, in mW; R is the signal strength received by the receiver, in dBm. Taking WiFi as an example, the received signal strength above -65 dBm can meet the needs of conventional wireless networks. The real-time RSSI received by the receiver is mainly affected by three aspects: path attenuation, occlusion and multipath effect.

2.3. Frequency modulated continuous wave (FMCM)

FMCW is a continuous wave signal. Generally, pulse radar signal has high peak power and small duty cycle, while continuous wave radar can have 100% duty cycle and low power. FM continuous wave radar continuously transmits FM signals to measure the range, angle and speed of targets. Its working principle is as follows: first, the synthesizer generates a linear frequency modulation pulse, which is transmitted by the transmitting antenna, and the reflection of the target object on the linear frequency modulation pulse generates a reflected linear frequency modulation pulse captured by the receiving antenna. The mixer combines the received signal and the transmitted signal to generate an intermediate frequency signal. Generally speaking, a radar contains multiple transmit and receive antennas, so it will also get multiple if signals. The information of the target object is contained in these intermediate frequency signals. By performing multiple discrete Fourier transforms on the intermediate frequency signals, these information can be separated. The generated data can be processed by filtering algorithm to generate point clouds, or directly input into the deep learning model as a data block to judge the target distance, angle and speed.

3. The process of wireless signal sensing

3.1. Signal acquisition: strategies and techniques

Signal acquisition forms the initial step in sensing through wireless signals. The effective collection of signals containing human motion information directly influences the quality of identity recognition. A typical wireless signal acquisition device usually comprises a transmitter and a receiver. The transmitter is commonly a commercially available WiFi device, while the receiver is typically a computer equipped with a wireless network card. Currently, Received Signal Strength Indicator and Channel State Information are the main conveyors of human motion characteristic signals in WiFi perception [4]. In comparison to RSSI, which has limited perceptual granularity, CSI presents several advantages. First, CSI exhibits heightened sensitivity to changes in the surrounding environment, offering high-precision information. It facilitates fine-grained perception, better aligning with future research application requirements. Second, CSI encompasses the amplitude and phase information of each subcarrier, providing researchers with a wealth of data. Third, due to the utilization of Orthogonal Frequency-Division Multiplexing (OFDM) technology, CSI is less affected by multipath effects.

The comparison between RSSI and CSI is illustrated in Figure 1. The CSI information can be conceptualized as RSSI information modulated by OFDM technology, thus encapsulating more comprehensive data.

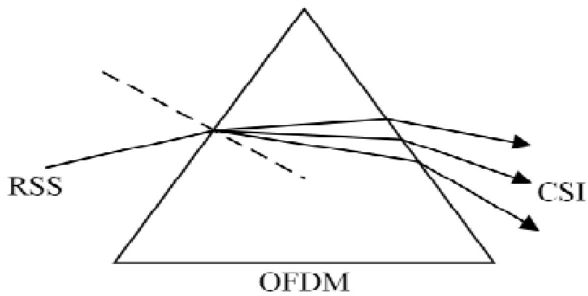

Figure 1. Relationship diagram of RSSI and CSI (Photo/Picture credit: Original).

To sum up, CSI has become the mainstream perception carrier in the current Wi Fi perception research due to its better detail perception ability and stronger anti-interference ability. By using the amplitude data and phase data in CSI information, there are many research results of identity recognition, such as WiWho, FreeSense [1].

3.2. Data pre-processing: importance and methods

Due to the instability of equipment operation and the impact of environmental uncertainty, the collected RSS or CSI data may contain a lot of noise. For Wi Fi sensing, effective preprocessing of the collected signal is a necessary condition for successful sensing. The collected signal preprocessing generally includes noise removal, feature dimensionality reduction and other operations. The purpose is to remove interference factors, screen the main perceptual features, and provide high-quality data basis for later feature extraction operations.

3.2.1. Noise removal. According to the order of information processing, the commonly used noise removal methods mainly include outlier removal, filtering and so on.

Outlier removal. Due to the change of the internal state of the equipment (such as transmission power, transmission rate, etc.), the signal will have obvious mutation, forming outlier information at the acquisition end. Outliers will cause abnormal signal disturbance, which will affect the identification results. The commonly used outlier detection methods are based on distance, statistics, density and offset. At present, the commonly used outlier removal algorithm is Hampel algorithm [1], which determines the information that is not within the specified range of the mean and standard deviation as outliers.

Low pass filtering. The low-pass filter can filter out the high-frequency signal and only retain the low-frequency characteristic information reflecting the disturbance of human action on Wi Fi. Butterworth and Gauss low-pass filters are commonly used. The transition of the ideal low-pass filter is very rapid, which will produce ringing phenomenon [2], while the Gaussian low-pass filter is relatively smooth, which will not produce ringing phenomenon. Butterworth low-pass filter, whose smoothness is between ideal low-pass filter and Gaussian low-pass filter, is the most commonly used filter in the preprocessing stage of wireless sensing field.

3.2.2. Feature dimensionality reduction. For the collected Wi Fi information, too many feature dimensions will make the feature matching process too complex and affect the recognition accuracy. Therefore, it is usually necessary to reduce the dimension of perceptual information in the data preprocessing stage. Principal component analysis is the main method of feature dimensionality reduction at present. It can transform the original data into a set of linear independent representations of each dimension through linear transformation, and can be used to extract the main feature components of the data. There are two implementation methods of PCA algorithm, which are based on eigenvalue decomposition covariance matrix and SVD decomposition covariance matrix.

3.3. Feature extraction: approaches and implications

Feature extraction is to select effective features from the target feature set. The preprocessed wireless sensing information contains the effective information that reflects the signal disturbance characteristics of human action. The feature is extracted, and then the classifier is trained for identity recognition. In Wi Fi perception, common features include statistical features, Doppler frequency shift features, wavelet transform features and time-frequency map features [3], as listed in Table 1.

Table 1. Comparison and Analysis of Feature Extraction Techniques in Wireless Signal Sensing.

Feature name	Principle of feature extraction	Feature analysis
Statistical Characteristics	Perform statistical analysis on the waveform of the collected original data	Low processing difficulty and clarity, but may overlook effective feature information
Dopplershift characterist-ics	Measurement of Doppler frequency shift characteristics caused by human movements	Has good distinguishability
Wavelet Transform Feat-ures	The motion frequencies of various parts of the human body are different, and wavelet transform can analyze signals on multiple frequ-ency scales	It can make the extracted features more refined
Time frequency diagram features	Using Short Time Fourier Transform (STFT) to transform WiFi signals into time-frequency maps, thus obtaining richer feature information	Rich signal feature information can be obtained and displayed directly, but it is difficult to process

3.3.1. Statistical characteristics. At present, the main statistical features used are the maximum, minimum, average, variance, mean square root and frequency distribution of the signal in the time domain, as well as the Fourier transform value, spectral probability, signal energy, spectral entropy and frequency peak of the signal in the frequency domain. Early researches on WiFi perception used statistical methods to extract signal features.

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3.3.2. Doppler shift characteristics. When detecting identity information in indoor environment, the human body needs to complete some actions, which often cause Doppler frequency shift.

3.3.3. Wavelet transform features. Wavelet transform can analyze signals on multiple frequency scales, and has better extraction ability for local fine features.

3.3.4. Time frequency diagram features. By using short-time Fourier transform (STFT) and other algorithms, the action signal can be transformed into a time-frequency map to obtain more abundant feature information, so as to achieve more precise recognition.

3.4. Classification and identification: algorithms and applications

After the database template is established for each action extraction feature, the newly collected sensing signal can be analyzed and recognized. The perceptual recognition methods of human identity can be divided into direct recognition and classifier recognition. The direct recognition method usually uses the Dynamic Time Wrapping (DTW) algorithm to directly calculate the similarity between the newly acquired signal and the model and find the closest classification. Classifier recognition uses a supervised learning method. First, collect data and label classification tags, train the classifier as a training set, and then use the trained classifier to identify the newly acquired sensory signals. Currently used classification methods are support vector machine (SVM), K-nearest neighbor (KNN) and deep learning methods. At present, in the field of Wi Fi perceived identity, the comparison of research results using machine learning algorithm and deep learning algorithm is shown in Table 2.

Table 2. Comparison chart.

Algorithm category	Algorithm name	Algorithm principle	advantage	disadvantage	Typical applications
Machine learning algorithm	DTW	Calculate the similarity between time series data by extending and shortening	No training required, fast matching	Large amount of calculation; Strong dependence on templates	FreeSense
	KNN	The sample category is the category of the nearest K samples	Simple, easy to understand and implement	When the data samples are unevenly distributed, the performance decreases; Too much storage space	MAIS，FreeSense
	SVM	Solve the separation hyperplane which can correctly divide the training data set and has the largest geometric interval	High precision and good generalization ability	Not suitable for large sample data	Wifiu

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Table 2. (continued).

Deep learning algorithm	LSTM	Through the gating mechanism, the recurrent neural network is used to model the long-term context and other relationships	Suitable for processing time series data; It can solve the problem of long-term lack of RNN dependence	Classifier training is time-consuming	LSTM
	GRU	The simplified version of LSTM uses the hidden state to transmit information	Compared with LSTM, the parameters are reduced; Not easy to over fit	Better performance of LSTM in dataset	GRU
	CNN	Extracting multi-dimensional perceptual signal features after time series data reconstruction by convolution kernel	It can extract the disturbance characteristics of gait to the signal between subcarriers, and has strong perception ability	Classifier training is time-consuming	CNN

In the research of identity recognition based on WiFi signal, the classification and recognition of identity information is usually the last stage of the research, and it is also a necessary link to verify the advantages and disadvantages of the designed model. Whether it is traditional machine learning or deep learning, it is necessary to train a large number of classifiers in advance to form a template for testing the recognition effect in the later stage. In addition， the classifier often needs to consider whether the application scenario is binary classification or multi classification. Combined with the actual situation of Wi Fi perception of identity， identity recognition applications are mostly a multi classification problem. Generally speaking, logistic regression and SVM are often used to solve binary classification problems; For multi classification problems, the softmax function is often used to solve them.

4. Research on application scenarios

4.1. Human presence detection

In recent， many human presence detection methods based on wireless sensing have been proposed. According to the composition of the system, they can be divided into two categories: one is the detection method based on supervised learning; The other is the detection method based on unsupervised learning.

4.1.1. The detection method based on supervised learning. Many existing indoor human presence detection based on wireless sensing focus on supervised learning detection methods. Because CSI in the physical layer can capture the channel frequency diversity of signals caused by the environment, human activity can be judged in real time by detecting the movement of CSI characteristic mode.

As people pass through the room, taking into account the selective frequency fading characteristics of the internal wireless channels and eliminating the impact of power level fluctuations in wireless equipment on power consumption, Brauers et al. proposed a method to detect the presence of moving objects using CSI. A key component of the system is the use of screening features related to the motion of screening objects. Relevant features are extracted by using the calibration steps required to calculate the covariance matrix. This method can only detect the moving objects in the environment. In view of this limitation, Han et al. proposed a passive indoor human detection based on CSI frequency domain fingerprint, which can generate the characteristic fingerprint by extracting the fine-grained physical layer channel state information, and then determine the human behavior in the environment by matching the on-line fingerprint with the off-line fingerprint [4]. The system can detect both moving and stationary states. The human body detection scheme proposed by Ding et al.only uses the phase difference information of CSI as the measurement, and uses support vector machine, random forest and k-nearest neighbor machine learning classification algorithm to detect the intrusion, with high detection accuracy.

4.1.2. The detection method based on unsupervised learning. For more realistic situations, supervised learning systems don't work as designed. More specifically, an activity may be considered abnormal when it first appears, but when more and more activity is observed, it may be considered normal. Because not all anomalous activities can be defined in advance, and the concept of anomaly also depends on the frequency of observation.

A non-intrusive anomalous activity sensing system proposed by WarnFi, Pang et al [5]. use only two commercial WiFi equipments. The system works by uniquely changing the time series of CSI when the body blocks the wireless signal sent from the access point to the receiver. By using a nonparametric model, we can dynamically cluster abnormal perceptions of human activities. The calculation process of the non-parametric model is as follows: the density-based mean shift clustering method is adopted, and monitoring information is not required as an input parameter. The bandwidth of the search window does not need to be defined in advance, it is calculated by formula (3).

$$l_{i=\|x_{i-}x_{i,n/2}\|} \tag{3}$$

Where $x_{i,n/2}$is the m/2 nearest neighbor of CSI featurex_i (i=1, ..., m). The clustering method is carried out as follows:

1) New center of CSI properties in the calculation window:

$$\widetilde{x_\iota} = \frac{\sum_{j-1}^{m} x_i g\left(\left\|\frac{x_i - x_{i,j}}{l_i}\right\|^2\right)}{\sum_{j-1}^{m} g\left(\left\|\frac{x_i - x_{i,j}}{l_i}\right\|^2\right)} \tag{4}$$

Where: $x_{i,j}$are CSI features inx_i search window; $g(x) = q'(x)$is the core of CSI characteristic density estimation x_i.

2) Starting from $\widetilde{x_\iota}$， repeat step 1) until convergence.

In order to solve the problem of system stability at different motion speeds, Liu et al.used the state information of the physical layer of the wireless network to extract the characteristics of channel fluctuations, and used probability technology to detect human motion, using hidden Markov model as a classifier, making human detection a probability problem. The system is more accurate in human detection, and can maintain the stability of the system at different speeds.

4.2. Behavior Recognition

4.2.1. Gait based identity recognition. Research shows that gait can be used as an important biological feature of human identity recognition [6]. Gait based identity recognition technology collects the dynamic characteristics of organisms, which is richer than the static characteristics. Due to the differences in body shape and movement mode, gait disturbs the WiFi signal in the region in a unique way, resulting in a high recognition characteristic response on the received signal [7]. In recent years, the technology of gait recognition based on wireless signal continues to progress, relevant research results continue to emerge, and the recognition effect is getting better and better.

2016 can be said to be the first year of the development of gait recognition technology based on Wi Fi perception. This year, typical gait recognition methods based on traditional machine learning such as WiWho, WiFiU and WiFi-IDwere proposed.The above three identification methods have their own advantages and disadvantages. Although the recognition accuracy of WiWho is high, it requires the tester to move in a straight line in a specific area, and the description of gait features is not accurate enough, which leads to a rapid decline in the recognition accuracy after the group size increases; The innovation of WiFiU is that it can convert the original Wi Fi timing signal into a high fidelity spectrum, and then it can use the mature classification methods in the field of image, but it does not perform well

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on a large group of data sets; WiFi-ID uses the mute elimination algorithm to determine the length and starting point of the effective area for the original data, and the recognition accuracy is relatively high, but it does not consider the recognition scheme of non Los path, nor does it consider the larger recognition group and the robustness of recognition.

Since 2019, in order to more accurately characterize and extract behavior perception features, deep learning algorithms have been widely introduced into the research of identity recognition based on Wi Fi perception, and a series of algorithms with higher recognition accuracy have emerged, such as WiId [7], CSIID, Deep WiId. The above three methods have their own characteristics. Among them, WiId uses deep neural network for feature extraction and classification for the first time, which not only improves the accuracy, but also effectively reduces the workload of data preprocessing; According to the short-term characteristics of the behavior perception mode, csiid uses the long-term and short-term memory network (LSTM), which solves the problem of gradient explosion or disappearance in the RNN model when dealing with the long-term correlation problem [8]; The structure of deep WiId is similar to that of WiId, but it has higher recognition accuracy and stronger robustness, which can be said to be an improvement of WiId model.

To sum up, in the research process of gait based identity recognition using Wi Fi signals, the use method has changed from machine learning to deep learning, and the recognition accuracy has also increased from 80% to more than 98%. After the recognition accuracy is ideal, the lightweight of the model has also attracted more and more attention. However, at present, most of these researches can only recognize single person in Wi Fi scenes, while there are few researches on multi person recognition. In the future, multi person recognition and model lightweight may become the focus of Wi Fi perceptual identity research.

4.2.2. Gesture based identity recognition. As both gesture and gait characteristics fall under the umbrella of behavioral features, it's noteworthy that even the same gestures tend to manifest with unique differences among individuals. This provides us with a potential means for identity recognition [9]. In 2018, as WiFi sensing data acquisition and processing methodologies began to mature, we witnessed the emergence of gesture recognition systems or methods anchored on traditional machine learning techniques such as WiId and SIWI. WiId and SIWI share similar philosophies in their approach to identity recognition. Each predefined gesture behavior is assigned a unique classification model correlating to a specific user identity [10]. Moreover, SIWI's proposed CSI segment segmentation mechanism can extract finer feature information and employ the Fresnel model to discern the user's behavior distance and direction, thereby enhancing gesture recognition efficacy. Despite these advancements, limitations persist for WiId and SIWI, such as a large sample data requirement and a narrow variety of recognizable actions. Post-2020, the extensive application of deep learning technology in gesture recognition models led to a shift in focus towards model lightweighting. This period saw the advent of identification methods like FingerPass and WiHF, each developed around different deep learning model designs. FingerPass employs a lightweight network for high-precision user recognition, while WiHF exhibits significant advantages in cross-scene gesture recognition and user identification. In terms of feature information, both methodologies fully leverage the amplitude and phase information inherent in CSI data.

4.3. Passive location

With the use of technologies such as MIMO, the number of antennas on commercial WLAN devices continues to increase. Inspired by array angle measurement technology, using CSI measurement values for angle of arrival estimation has become popular on Wi Fi devices. If AoA is determined relative to multiple known base stations, the position of the terminal can also be estimated through angle intersection.

In indoor Wi Fi communication scenarios, the distance between the terminal and the base station is usually much greater than the antenna spacing d, and the incoming signals on each antenna can be considered parallel. If the angle between the antenna array and the input signal is θ， The phase difference between the arrival phase of the nth antenna signal and the arrival phase of the first antenna signal is:

$$\Delta\varphi_n = 2\pi nd \cos\theta \cdot f/c \tag{5}$$

Where, f is the carrier frequency; $c$is the speed of light. In theory, a set of phase differences can be obtained from CSI measurements$\Delta\varphi$， By combining information such as known antenna spacing d, the angle of arrival can be directly calculatedθ。 However, due to the presence of noise and multipath interference, it is not possible to directly solve equation (5) to obtain an accurate solution θ. At present, CSI based AoA estimation mainly utilizes the characteristic of multiple antennas in base stations, and there is a clear relationship between the phase difference between antennas and AoA. Due to multipath and other factors, the more antennas there are, the more accurate the calculated angle of arrival will be. However, considering cost and volume, the existing commercial Wireless network interface controller or WiFi devices usually do not have many antennas. Implementing applications based on existing WiFi devices is still an effective means of promotion. With the development of WiFi protocols and the advancement of antenna design and technology, there will be more available antennas in the future, and the accuracy of the AoA method will also be further improved. At the same time, the AoA method is based on a strict mathematical model, and the accuracy of the phase information used will directly affect the accuracy of the results. Although many systems, including Phaser and SpotFi, have made some error processing on the phase extracted from CSI, the original data obtained is limited by the platform and tools, There is still room for further discussion on the error sources and their processing methods.

5. Challenges in wireless sensing with 6G

5.1. Multi person identification

In the wireless signal sensing information carrier, although CSI information can provide more fine-grained sensing features than RSSI information， it is still greatly affected by the multipath effect. When there are multiple individuals in the environment covered by wireless signals, the sensing signals collected by the receiver include not only the multipath signals of surrounding obstacles, but also the multipath signals generated by mutual reflection between human bodies. Therefore, when the distance between human bodies is small, the receiver may mistake multiple people for a single person as a whole， resulting in multiple person recognition failure. In real life， multi person perception scenarios are widespread and have objective application requirements.

5.2. Transfer learning

Because wireless signal perception is seriously affected by multipath effect, although the current perception methods based on machine learning or deep learning can achieve high recognition accuracy after training in a fixed indoor environment, the recognition accuracy will drop sharply when switching to other indoor environments. As shown in Figure 2, when doing the same action in different indoor environments, the CSI information obtained varies greatly. Therefore, exploring the commonness of human gait or movement in different environments, establishing an effective migration perception mechanism, and realizing cross environment no training migration or a small amount of training migration are the key problems to be solved in the future of wireless signal perception.

6. Conclusion

This paper offers an in-depth exploration of the cutting-edge research advancements in the domain of wireless sensing, specifically focusing on technologies utilizing indoor wireless signals. At the core of our investigation is a comprehensive analysis of the critical technologies shaping the landscape of wireless sensing. This analysis is conducted with an intent to uncover the underlying mechanisms, the intricate processes, and the multifaceted algorithms that facilitate this advanced mode of sensing. An extensive examination of the wireless sensing process is presented, from the initial phases of signal acquisition to the final stages of interpretation and application, providing readers with a panoramic view of the journey that the wireless signal embarks upon within the sensing framework. Furthermore, in our quest to provide a complete picture of the wireless sensing sphere, we lay bare the specific challenges that the current state of technology presents. These challenges range from technical hurdles to methodological obstacles, and their resolution forms the bedrock of the future evolution of this field. By presenting these challenges, we aim to spur forward-thinking discussions, innovative problem-solving, and robust advancements in the domain of wireless sensing.

References

[1] Ma Y, Zhou G, Wang S. WiFi sensing with channel state information: A survey[J]. ACM Computing Surveys (CSUR), 2019, 52(3): 1-36.
[2] Kellner, E., Dhital, B., Kiselev, V. G., & Reisert, M. (2016). Gibbs‐ringing artifact removal based on local subvoxel‐shifts. Magnetic resonance in medicine, 76(5), 1574-1581.
[3] Yu W Y, Wang S H, Zhang Y D. A survey on gait recognition in IoT applications[J]. EAI Endorsed Transactions on Internet of Things, 2021, 7(28): e3-e3.
[4] Gaszczak A, Breckon T P, Han J. Real-time people and vehicle detection from UAV imagery[C]//Intelligent robots and computer vision XXVIII: algorithms and techniques. SPIE, 2011, 7878: 71-83.
[5] Abolhassani S S, Zandifar A, Ghourchian N, et al. Improving residential building energy simulations through occupancy data derived from commercial off-the-shelf Wi-Fi sensing technology[J]. Energy and Buildings, 2022, 272: 112354.
[6] Stevenage S V, Nixon M S, Vince K. Visual analysis of gait as a cue to identity[J]. Applied Cognitive Psychology: The Official Journal of the Society for Applied Research in Memory and Cognition, 2023, 13(6): 513-526.
[7] Li H, Yang W, Wang J, et al. WiFinger: Talk to your smart devices with finger-grained gesture[C]//Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing. 2016: 250-261.
[8] Li H, Yang W, Wang J, et al. WiFinger: Talk to your smart devices with finger-grained gesture[C]//Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing. 2016: 250-261.
[9] Pegoraro J, Lacruz J O, Meneghello F, et al. RAPID: Retrofitting IEEE 802.11 ay access points for indoor human detection and sensing[J]. IEEE Transactions on Mobile Computing, 2023.
[10] Avellar L, Stefano Filho C, Delgado G, et al. AI-enabled photonic smart garment for movement analysis[J]. Scientific reports, 2022, 12(1): 4067.