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Contactless Electromagnetic Human Sensing for Biomedical and Healthcare Applications

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ABSTRACT: Contactless electromagnetic (EM) sensing has revolutionized biomedical and healthcare applications, enabling noninvasive, real-time monitoring and diagnosis of physiological conditions. Unlike traditional wearable or invasive sensing solutions leading to patient discomfort, contactless EM sensing provides a seamless and unobtrusive solution for continuous health monitoring. This review categorizes EM sensing into imaging-based and signal-based approaches, emphasizing recent technological advancements. Imaging-based sensing techniques provide high-resolution imaging of human anatomy for analysis and diagnosis, while signal-based methods infer physiological conditions through the variations in EM signals caused by human movements. Particularly, metamaterials have significantly enhanced contactless EM human sensing due to their superior ability to precisely manipulate EM waves. Metamaterial-based imaging, such as Magnetic Resonance Imaging (MRI), improves diagnostic accuracy by enhancing imaging contrast and reducing noise. Meanwhile, metamaterial-based sensing, exemplified by metasurface-enabled multi-person vital-sign detection, offers increased spatial resolution and signal-to-noise ratio, enabling reliable and efficient human health monitoring. Furthermore, the integration of metamaterials with artificial intelligence (AI) has transformed EM human sensing, enhancing its accuracy and adaptability across various environments. By highlighting recent progress and discussing future challenges, this review underscores the importance of further research to unlock the full potential of EM sensing in advancing biomedical and healthcare technologies.

1. INTRODUCTION

Electromagnetic (EM) human sensing has emerged as a pivotal frontier in biomedical and healthcare (B&H) applications, offering unprecedented potential for monitoring and diagnosing a spectrum of human physiological conditions [1]. As the world grapples with an aging population and the escalating prevalence of chronic diseases, there is an acute demand for innovative healthcare solutions to facilitate continuous and real-time health monitoring. Fig. 1 presents an overview of physiological measurements for diverse B&H applications, mapping key body regions to their associated physiological signals. Besides, this figure highlights the specific applications, such as brain activity analysis and fall detection, along with the gold-standard sensors used for monitoring these physiological signals. Based on the sensors used, the existing EM human sensing technology can be categorized into three types: wearable, implantable, and contactless, as shown in Fig. 2. Each of the three sensing modalities offers distinct strengths and weaknesses. Wearable sensors are noninvasive and flexible in design, providing comfort and adherence. However, their performance can be affected by user compliance and variability in usage. Implantable sensors deliver precise and continuous monitoring, but they are invasive and require maintenance, which limits their lifespan. Contactless sensors, on the other hand, are noninvasive and suitable for wide-area monitoring and through-wall surveillance, but they face challenges such as signal attenuation. Meanwhile, contactless optical-based sensors are generally faced with privacy concerns.

EM human sensing technology leverages the power of EM waves to penetrate various media and interact with biological tissues, thereby enabling the remote detection and analysis of vital signs and other health-related metrics. In Fig. 3, we provide a roadmap charting the progression of EM human sensing for B&H applications from 1972 to 2024. This figure traces the progression of EM sensing and imaging technologies in biomedical applications, spanning from early innovations like microwave sensing for physiological movements to recent advancements in intelligent metasurface-based systems. Specifically, in 1972, Johnson and Guy [2] introduced non-ionizing EM wave effects in biological systems, covering RF/microwave and optical effects, including applications and measurements. Then, Kim and Ling [3] proposed a human activity recognition approach leveraging the radar micro-Doppler effect in 2009, which could be applied to elder fall detection. In 2019, Li et al. [4] presented an intelligent EM metasurface for real-time and high-resolution sensing of human body language and vital signs using Wi-Fi signals at 2.4 GHz. Furthermore, the red markers in Fig. 3 represent the work on contactless human sensing, while the blue markers represent the other EM human sensing work. It is worth noting that there has been increasing work on contactless EM human sensing in the last decade, ranging from glucose monitoring to intelligent vital-sign monitoring, reflecting the growing trend of utilizing EM sensing for noninvasive healthcare solutions. Additionally, the integration of AI and machine learning algorithms has also enhanced the

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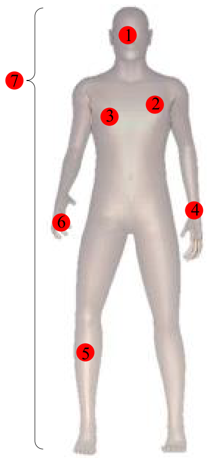


Physiological Signal Measurement for Biomedical and Healthcare Applications

Markers	Organs&Tissues	Physiological Signal	Applications	Gold-standard Sensor
1	Head	Head Position and Movement, and brain wave	Brain activity monitoring, brain disease diagnosis	Camera, Electroencephalogram
2	Heart	Heartbeat	Vital-sign monitoring	Electrocardiograph
3	Lungs	Respiration	Vital-sign monitoring	Oximeter, pressure belt
4	Carotid Pulse	Heart rate and blood pressure	Vital-sign monitoring	Electrocardiograph
5	Legs	Gait	Fall detection, elder care	Inertial Measurement Unit, Camera
6	Hands	Hand Gesture	Assisted living, remote control	Camera
7	The Whole Body	Posture and Activity	Assisted living, activity recognition, remote monitoring	Camera, Inertial Measurement Unit

FIGURE 1. Measurement of detectable biomedical signals, along with the corresponding human organs and gold-standard sensors.

FIGURE 2. Categories of EM-based human sensing technologies, showcasing contactless, wearable, and implantable approaches, their advantages, limitations, and diverse applications in B&H domain.

diagnostic accuracy and predictive capabilities of these contactless sensing systems.

Furthermore, the existing contactless EM human sensing technologies can be classified into two categories: imaging-based and signal-based sensing. The imaging-based sensing strategy aims to assess human health status by imaging the body and tissues, while the signal-based sensing counterpart infers the human body's behavior and health state by quantitatively or qualitatively extracting the influence of human physiological movements on EM signals. Furthermore, to enhance the sensing ability of both the imaging-based and signal-based systems, metamaterials [5, 6] have been increasingly adopted to the realm of contactless EM human sensing. Metamaterials are artificial structures known for exceptional physical properties, extending beyond those of conventional natural materials [7–9]. Crafted from periodically or quasi-periodically arranged unit cells, metamaterials could precisely control the radiation, scattering, and propagation of EM waves, thus enhancing the contactless human sensing ability of EM waves.

Here, we focus primarily on contactless EM human sensing and provide a detailed analysis of the history, advancements, and applications of this technology, highlighting its transformative impact on the B&H landscape. Specifically, we categorize EM sensing into imaging-based and signal-based approaches, emphasizing their advancements, respectively. Imaging-based sensing techniques provide high-resolution imaging of human anatomy for analysis and diagnosis, while signal-based methods infer physiological conditions through the variations in EM signals caused by human movements. Particularly, we also explore the role of EM metamaterials in contactless human sensing and imaging technologies, and overview the existing metamaterial-based human sensing systems in detail.

1.1. Existing Reviews and Surveys

A variety of reviews on EM human sensing for B&H applications have been published in the last five years, as summarized in Table 1. For instance, Zhou et al. [10] overviewed the existing EM medical imaging technologies utilizing deep learning (DL), including traits, tech trends, case studies, challenges, and future promise. Kong et al. [11] reviewed millimeter wave (mmWave) radar-based human sensing systems, including the dedicated hardware, signal processing, applications, and future research directions. Ma et al. [12] surveyed Wi-Fi based human sensing using Channel State Information (CSI). This paper detailed the principle, basic paradigm, and applications of Wi-Fi sensing, thus proving the feasibility and effectiveness of using wireless communication signals to perceive human activities. However, the existing literature predominantly provided a general overview of EM sensing for healthcare applications, seldom delving into a comprehensive introduction to the contactless sensing technique in the realm of B&H.

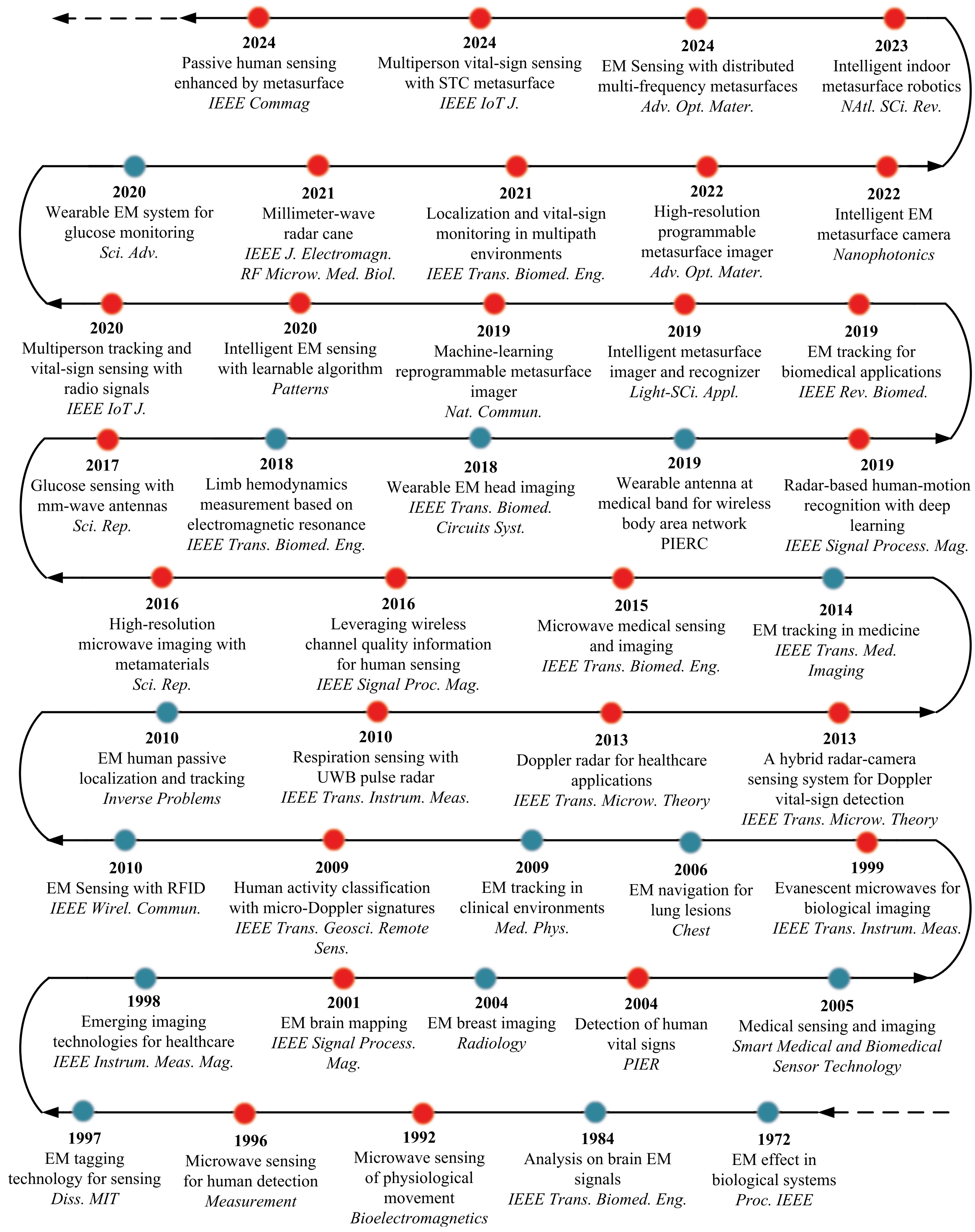


FIGURE 3. Roadmap charting the progression of EM human sensing for B&H applications from 1972 to 2024. The red markers represent the work on contactless human sensing, while the blue markers represent the other EM human sensing work. It can be seen that there has been an increase in the work on contactless EM human sensing in the last decade.

- To our knowledge, there have been a range of reviews on different contactless human sensing, spanning from the conventional radar-based [18, 22] to the emerging Wi-Fi based sensing [12, 21]. Nevertheless, there are few review articles thoroughly summarizing these sensing technologies.
- The majority of reviews concentrated on a general summary of EM human sensing for B&H applications. However, there is a notable lack of surveys and reviews specifically dedicated to contactless EM human sensing and its biomedical applications [30, 31].

TABLE 1. The off-the-shelf reviews and surveys on EM human sensing for B&H applications.

Technology	Year	Authors	Scope
Medical imaging	2021	Zhou et al. [10]	DL in Medical Imaging, including technology trend, case studies, and future directions.
	2021	Fields et al. [13]	Discussing the utility of CT, MRI, and PET in visualizing the characteristic features of COVID-19 pneumonia.
	2021	Hermessi et al. [14]	An overview of medical image fusion, including pixel-level, feature -level and decision-level fusion methods.
	2023	Li et al. [15]	A comprehensive review of the state-of-the-art Transformer-based approaches for medical imaging.
	2024	Abhisheka et al. [16]	Detailed analysis of the working principles, benefits, and limitations of diverse imaging modalities.
Radar-based sensing	2019	Fioranelli et al. [17]	Case studies of radar used to support health-care provisions, such as vital-sign monitoring and daily activity recognition.
	2019	Li et al. [18]	Portable radar-based human activity recognition with the assistance of DL technologies.
	2020	Cardillo et al. [19]	MIMO technology and its applications on the vital sign detection and human localization.
	2023	Zhang et al. [11]	mmWave-based human sensing works, as well as the mmWave hardware platforms and some key techniques of mmWave sensing.
	2024	Kong et al. [20]	mmWave radar-based sensing techniques and applications in autonomous vehicles, smart homes, and industry.
WiFi-based sensing	2019	Liu et al. [21]	The existing WiFi sensing systems in terms of their basic principles, techniques and system structures.
	2019	Ma et al. [12]	A comprehensive review of the signal processing techniques, algorithms, applications, and performance results of WiFi sensing with CSI.
	2021	Nirmal et al. [22]	DL techniques, architectures, and algorithms recently applied to WiFi-based device-free human sensing.
	2022	Tan et al. [23]	Evolution of WiFi sensing systems utilizing commodity devices in three applications: activity recognition, object sensing and localization.
	2023	Chen et al. [24]	Recent research efforts on cross-domain WiFi Sensing, i.e., how to ensure sensing performance when exposing a pre-trained system to new domains.
Metamaterial-based sensing	2020	Zhang et al. [25]	Metasurface-empowered bioimaging and biosensing, including but not limited to metasurfaces for chiral imaging, super-resolution imaging, and magnetic resonance imaging.
	2022	Zhang et al. [26]	Incorporation of RIS into wireless human sensing and localization systems, including key challenges and enabling techniques.
	2023	Razzicchia et al. [27]	Applications of metasurface in two medical microwave imaging systems: stroke detection and liver ablation monitoring.
	2024	Tzarouchis et al. [28]	Overview the state-of-the-art biomedical systems that utilize metamaterial concepts for enhancing their performance in some form or another.
	2024	Asokan et al. [29]	Applications of metamaterial-enhanced antennas in the realm of healthcare.

- Previous articles reviewing EM human sensing lack discussions on the metamaterial-based sensing technique, which has been garnering increasing interest due to the ability of metamaterials to flexibly manipulate emitted EM radiation [28, 32, 33].

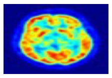
1.2. Contributions of Our Review

The research on the applicability of EM human sensing for B&H is progressing at a significant pace. In this case, a dedicated review of the contactless EM human sensing technology is required to cover the most recent research work. In contrast to the previous reviews, this study aims to comprehensively overview the recent advance of contactless EM human sensing in the B&H domain. We also introduce the technology of metamaterial-assisted human imaging and sensing, which is a distinctive feature that differentiates this review from prior existing surveys.

The multi-fold contributions of this work are as follows:

- This review provides a comprehensive overview of contactless EM human sensing and introduces the theoretical underpinnings of different EM sensing technologies, spanning from imaging-based to signal-based sensing.
- For the existing EM human sensing systems, we overview their applications in the B&H field and further introduce the advancements in sensor design, signal processing, and machine learning algorithms of these systems.
- Going a step beyond the existing EM human sensing reviews, we provide a detailed overview of the burgeoning metamaterial-based sensing technology, exploring the principles of EM wave propagation in these EM sensing systems and the benefit of metamaterials.

TABLE 2. Typical medical imaging techniques as well as their properties and applications.

Modality	Media	Properties
X-ray 	X-ray	Producing images of the body's internal structures, primarily to identify bone injuries, fractures, and other conditions.
PET 	Radioactivetracers	Detecting metabolic processes in the human body, and primarily used in oncology to detect cancer and study brain disorders.
CT 	X-ray	Providing detailed cross-sectional images of the human body, which can be reconstructed into three-dimensional images. It is useful for diagnosing internal injuries, tumors, and blood clots, as well as for guiding biopsies and surgical procedures.
MRI 	Magnetic fields	Producing detailed images of soft tissues, which makes it particularly effective for imaging organs, muscles, and the brain.

Applications of Medical Imaging	Functions
Multimodal medical image fusion	Combining information from multiple images to create a single image that provides more comprehensive information than any of the individual source images alone.
Medical image segmentation	Dividing an image into multiple segments to simplify and/or change the representation of an image.
Medical image translation	Transforming medical images from one modality to another without actually performing the second type of imaging scan.
Computer-aided diagnosis	Combining computer vision with radiological and pathology to assist medical image interpretation.

2. IMAGING-BASED CONTACTLESS SENSING

EM human imaging employs radio frequency waves to generate images of the human body, capturing both superficial and deeper structures without the need for physical contact. This technology has been widely applied to the areas that require a deep understanding of human body tissues safely and efficiently, including medical diagnostics, healthcare, security screenings, and rescue missions. Next, three typical imaging technologies, including medical imaging, radar-based imaging, and metamaterial-based imaging as well as their applications, will be overviewed.

2.1. Medical Imaging Technology

Medical imaging, as a noninvasive method for visualizing internal body structures, has been playing an important role in disease prediction and diagnosis [34]. There is a wide range of EM medical imaging solutions, e.g., X-ray radiography [35], magnetic resonance imaging (MRI) [36], computed tomography (CT) [37], and positron emission tomography (PET) [13]. Due to the differences in operating mechanisms and imaging principles listed in Table 2, these imaging techniques are suitable for diagnosing different diseases.

2.1.1. Traits of Medical Imaging

Medical imaging, with its high pixel resolution, offers noninvasive and detailed visualization of internal body structures, facilitating early diagnosis and treatment [38, 39]. It enhances clinical decision-making by providing detailed images of anatomy and pathology, allowing for more accurate assessments. Medical imaging also reduces the need for exploratory surgery, leading to faster recovery times and better patient outcomes. However, analyzing medical images typically requires extensive expertise and experience [40]. The main reasons are as follows. First, the diverse manifestations of diseases complicate medical image analysis [41]. Even under the same imaging modality, a lesion can exhibit different appearances, with various shapes, sizes, densities, and boundaries [42]. Second, external factors such as the differences in imaging technology could also bring challenges to the interpretation of medical images [43]. Even for a specific technology, variations in equipment settings, manufacturer designs, and imaging mechanisms can influence the quality of the generated images [44]. Furthermore, medical images can be susceptible to noise and artifacts, complicating their interpretation [45].

2.1.2. Applications of Medical Imaging

To aid in disease diagnosis using medical imaging and alleviate the burden on doctors, machine learning (ML)-based intelligent diagnostic methods have been extensively researched [46]. ML-aided medical imaging analysis could automatically give a preliminary diagnosis without human intervention, significantly improving the efficiency of medical treatment. Meanwhile, ML provides quantitative analysis and decision support [47], making clinicians more informed and precise diagnoses.

TABLE 3. Typical radar-based contactless human sensing systems for B&H applications.

Categories	Ref.	Radar Principle	Center Frequency (F) Bandwidth (B)	Applications
Imaging-based	[61]	UWB radar	F: 3.45 GHz B: 2.5 GHz	Microwave imaging of the cardiovascular system
	[62]	UWB radar	F: 3.5 GHz B: 3 GHz	Microwave imaging of breast cancer
	[63]	UWB MIMO radar	F: 1 GHz B: 1 GHz	3D imaging of moving individuals
	[64]	SAR	F: 330 GHz B: 30 GHz	Imaging of walking persons
	[65]	MIMO stepped-frequency CW radar	F: 65.5 GHz B: 7 GHz	Human imaging, vital-sign monitoring
Signal-based	[66]	UWB impulse radar	F: 7.25 GHz B: 2.5 GHz	Human fall detection
	[67]	mmWave FMCW radar	F: 77 GHz B: 9 GHz	Human breathing detection
	[68]	UWB impulse radar	F: 4.3 GHz B: 1.7 GHz	Human movement direction determination
	[69]	FMCW radar	F: 7.3 GHz B: 750 MHz	Human Tracking&Respiration monitoring
	[70]	mmWave FMCW radar	F: 62 GHz B: 4 GHz	Long-term cardiac activity monitoring

A. Multimodal medical image fusion: Multimodal medical image fusion combines multiple images from different imaging modalities to create a more informative and detailed image, thereby increasing the clinical applicability of medical images [48]. Li et al. [49] proposed a multimodal medical image fusion framework *Laplacian Recomposition (LRD)*, which utilized a Laplacian decision graph decomposition scheme to enhance image details and reduce noise. Meanwhile, Tang et al. [50] presented a multimodal medical image fusion method *MATR* utilizing a multiscale adaptive transformer to improve feature extraction ability and fusion performance. Zhou et al. [51] developed a Hybrid-fusion Network (Hi-Net) to synthesize multi-modal MR images, which could learn a mapping from the existing modalities to the missing modalities.

B. Medical image segmentation: Image segmentation is an indispensable part of clinical diagnosis that involves dividing a medical image into multiple segments, where each segment represents a different object or structure of interest in the image. Hatamizadeh et al. [52] proposed an encoder-decoder architecture named *UNEt TRansformers (UNETR)* for 3-dimensional (3D) medical image segmentation. Specifically, the UNETR model employed a transformer as the encoder to extract global multi-scale information in the input 3D volume. Qin et al. [53] adopted the knowledge distillation mechanism and transferred the knowledge learned by a well-trained model to a lightweight image segmentation model. With knowledge distillation, the lightweight network could achieve satisfactory segmentation performance with high runtime efficiency.

C. Medical image translation: Medical image translation aims to transform medical images from one modality to another while preserving the intrinsic source content. Generative Adversarial Network (GAN) is a commonly utilized DL technique for medical image translation. For instance, Armanious et al. [54] presented a GAN-based image-to-image translation model by combining the adversarial training scheme with a non-adversarial loss. Meanwhile, Özbey et al. [55] proposed an adversarial diffusion model for image translation, which leverages conditional diffusion and an adversarial projector for high-fidelity synthesis, enabling unsupervised training on unpaired datasets.

D. Computer-aided diagnosis (CAD): Computer-aided diagnosis (CAD) combines computer vision with radiological and pathology, aiming at assisting medical image interpretation [56–58]. For instance, Aljuaid et al. [56] developed a computer-aided diagnosis method utilizing the deep transfer learning technique for breast cancer classification, achieving high accuracy on the public *BreakHis* dataset. Meanwhile, Fan et al. [59] introduced a DL framework that could identify multiple abnormalities in chest X-rays and assess cardiomegaly, outperforming senior radiologists. However, despite significant progress in DL-based CAD, there are still concerns and uncertainties about DL algorithms. Therefore, CAD based on DL techniques is useful for complementing human expertise, but cannot replace radiologists' diagnosis [60].

2.2. Radar-Based Imaging Technology

Radar imaging of the human body has garnered considerable interest in both civilian and military sectors due to its non-contact, penetrating, versatile, and privacy-preserving attributes. Considerable efforts have been made to achieve high-resolution radar-based human body imaging [61–63, 71, 72], which could be divided into two categories, i.e., multiple-input multiple-output (MIMO) radar-based and synthetic aperture radar (SAR)-based imaging. Some typical radar-based human imaging systems are provided in Table 3. Next, we will briefly introduce the basic principle of MIMO radar and SAR for human body imaging, and then overview the existing radar-based imaging systems.

2.2.1. Principle of Radar-Based Imaging

A. MIMO radar: MIMO radar employs multiple transmitting and receiving antennas to improve spatial diversity and achieve superior performance for human body imaging. The fundamental operating principle of MIMO radar involves the transmission of EM waves from multiple antennas and the reception of the scattered waves by a separate set of antennas. When the transmitted EM waves interact with the human body's tissues, the received signals from different receiving antennas contain information about these tissues' characteristics and the spatial distribution of the scatterers within the body. By employing some signal processing algorithms [73], MIMO radar systems can extract the information from received signals to form high-resolution images.

B. SAR: SAR [74] uses the motion of a moving radar platform to synthesize a large antenna aperture, which in turn significantly enhances the resolution of the radar images. The fundamental principle behind SAR involves the continuous signal transmission of a moving platform towards the target area. As the radar platform moves, the position of the antenna changes, leading to variations in the phase of the backscattered signal. The process of generating an image from the collected data involves complex signal-processing techniques. One of the most critical steps is focusing, which compensates for the motion of the radar platform. Algorithms such as chirp scaling [75] and back-projection (BP) [76] are commonly used to correct the distortions caused by the platform movement.

2.2.2. Applications of Radar-Based Imaging

In this section, we will introduce three typical B&H applications, i.e., disease detection, activity sensing, and vital-sign monitoring, using radar-based human imaging techniques.

A. Disease detection: Due to the low-cost and noninvasive characteristics, radar-based microwave imaging (MWI) has been widely applied to medical diagnoses, such as breast cancer and brain stroke detection [61]. For instance, Moloney et al. [71] introduced the first-in-human clinical trial of the microwave breast imaging (MBI) system *Wavelia system*, which could detect and localize breast tumors and benign lesions in a non-ionizing, noninvasive microwave imaging manner. Godinho et al. [62] proposed an MWI algorithm to detect Axillary Lymph Node (ALN) metastases, which is crucial for breast cancer staging. A monostatic radar at 2–5 GHz was employed in experiments to scan the axillary region, achieving a Signal-to-Clutter Ratio higher than 2.8 dB and a Location Error lower than 15 mm. On the other hand, resolution is one of the important measures of MWI system performance. To further investigate the relation between resolution and image quality, Naghibi and Attari [77] provided an analytical study on the resolution and image quality of radar-based microwave imaging systems for breast cancer detection.

B. Activity sensing: Due to the superior performance of detecting the existence, locating, and identifying the status of human targets, radar-based body imaging has been applied to the B&H field [64, 78]. Pan et al. [63] proposed a 3-dimensional (3-D) imaging algorithm of moving targets using an ultra-wideband (UWB) MIMO radar. To enhance the imaging ability, a reference channel-based motion compensation method and a modified Kirchhoff migration algorithm were presented. Meanwhile, Zhao et al. [72] presented a hierarchical human activity classification pipeline using a frequency modulation continuous wave (FMCW) radar with MIMO antennas. DL technique was utilized for angle-insensitive human motion and posture recognition, addressing limitations in classifying movements at unfavorable angles and static postures [79–81]. Meanwhile, Gui et al. [82] proposed a single-channel SAR imaging method for walking human screening, utilizing high resolution and short synthetic aperture time of terahertz (THz) radar to address motion blur and Doppler shift issues.

C. Vital-sign monitoring: Human vital signs such as heartbeat and breathing can be used as important indicators for the initial diagnosis of diseases and are of great significance in B&H applications. Radar-based sensing scheme does not cause skin irritation or discomfort as contact measurements do and has been widely applied to vital-sign monitoring [83, 84]. Feng et al. [85] presented a MIMO radar system for chest motion imaging and non-contact multitarget vital signs measurement. Furthermore, a 2-D digital beamforming is employed to enhance heartbeat detection robustness in complex environments. Li et al. [65] proposed a motion-robust and contactless heartbeat sensing method utilizing a 4-D imaging radar. The 4-D radar could simultaneously collect the 3-D spatial and 1-dimensional temporal information to perceive human heartbeat in the space-time dimensions. Sakamoto et al. [86] presented a 2.4-GHz continuous-wave (CW) radar system with a 2-D nine-element antenna array for accurately locating and imaging respiratory motion in sleeping subjects.

2.3. Metamaterial-Based Imaging Technology

2.3.1. Metamaterial in Imaging-Based EM Sensing

EM metamaterials offer unique opportunities for enhancing the performance of EM imaging techniques, which are vital tools in medical diagnosis [88]. Firstly, integrating metamaterials into imaging systems could enhance signal-to-noise-ratio (SNR) and improve imaging contrast, facilitating the detection of tiny anomalies within the body. Besides, metamaterials can be constructed to reduce the scattering and absorption of EM waves by biological tissues, leading to clearer images with less distortion. Moreover, metamaterials can precisely steer EM energy to specific regions, enabling faster data acquisition and boosting imaging efficiency [89].

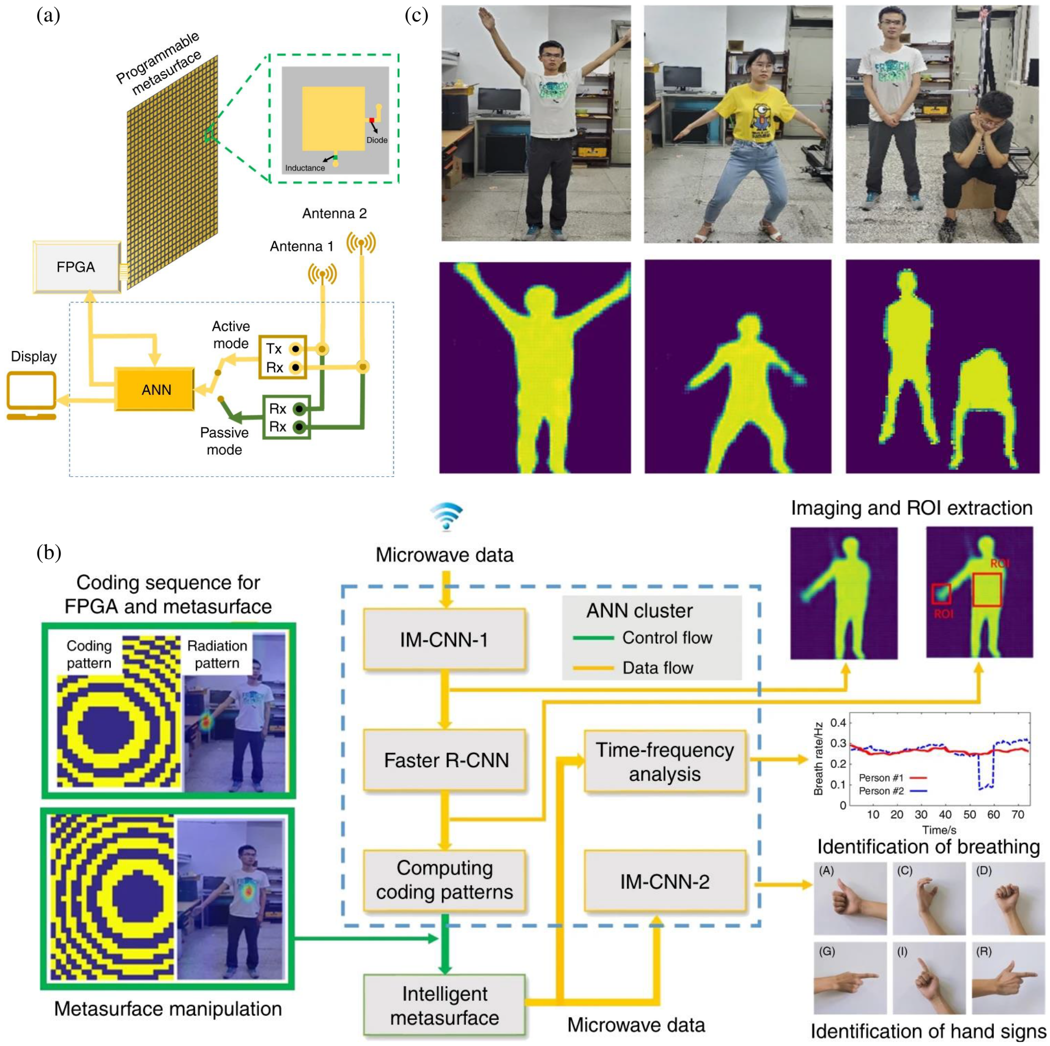


FIGURE 4. Metasurface-based human imaging and gesture recognition [4]. (a) System configuration for metasurface-based sensing. (b) The proposed DL model for human imaging and gesture recognition. (c) Human imaging results using the proposed system.

2.3.2. Applications of Metamaterial-Based Imaging

A. Metamaterial-based human body imaging: Metasurface-based imagers exploit the dynamic wave manipulation capability of the tunable meta-atoms to achieve high-resolution and real-time human imaging. This technique could significantly simplify the system by reducing the utilization of multiple antennas and complex signal processing, thereby lowering costs and power consumption. Darvazehban et al. [90] developed a metasurface antenna for EM torso imaging, which highlights the antenna's flexibility in pattern reconfigurability and efficient scanning for human body diagnostics. Meanwhile, the integration of ML improves the environmental adaptability of metasurface-based imaging systems, enabling dynamic adjustments to measurement modes for improved performance in diverse conditions [4, 91]. Specifically, as shown in Fig. 4, Li et al. [4] proposed a metasurface imager integrating artificial neural networks, which could achieve high-resolution body imaging and gesture analysis through adaptive data flow control.

B. Metamaterial-based MRI: Magnetic Resonance Imaging (MRI) is a noninvasive medical imaging technique renowned for its exceptional soft tissue visualization [92, 93]. However, MRI performance is often limited by low SNR and prolonged scanning times [94]. Metamaterials directly boost the signal strength within MRI systems through the capacity of finely manipulating EM fields, yielding clearer images [95]. Zhao et al. [96] developed an intelligent nonlinear metamaterial with a self-adaptive response for MRI, which could selectively amplify the magnetic field during the reception phase and enhance SNR. Additionally, the precise control over the magnetic field by metamaterials allows for fewer scans, in turn boosting imaging efficiency [97]. Lippke et al. [98] developed a reconfigurable metasurface for MRI, enabling precise electronic tuning to the Larmor frequency and the ability to concentrate magnetic fields within the target region.

C. Metamaterial-based MWI: Microwave Imaging (MWI) utilizes microwave signals to generate images of the body's internal structures. However, the resolution, SNR, and imag-

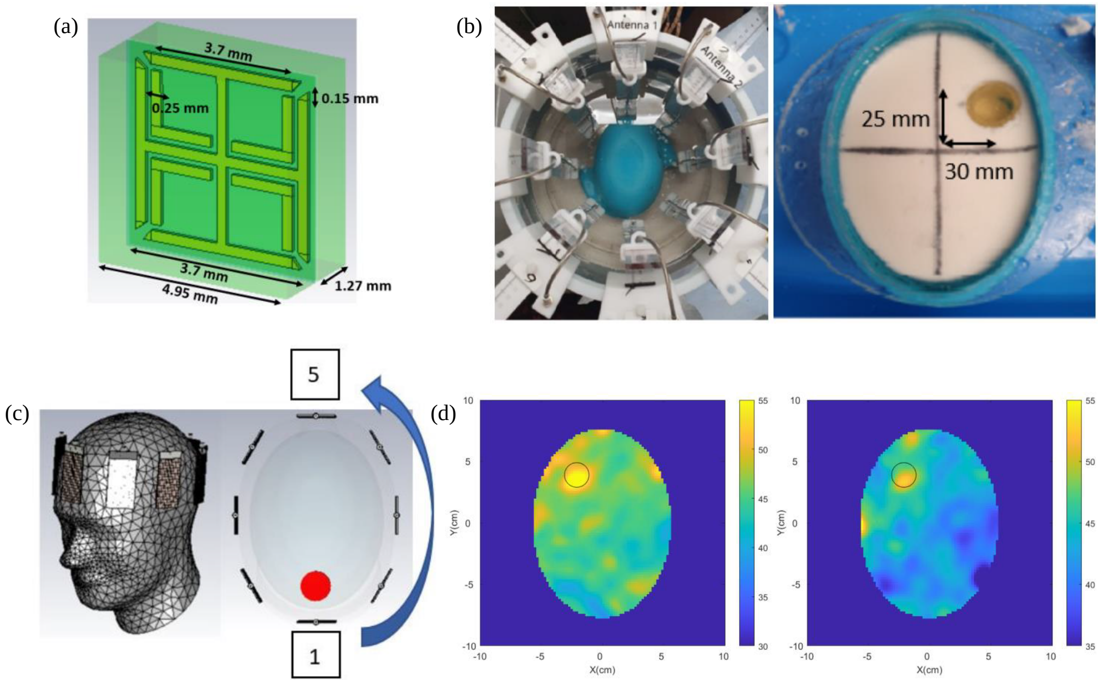


FIGURE 5. Metasurface-based MWI for brain stroke detection and localization [87]. (a) The proposed MTS unit cell. (b) Customized tomographic experimental setup. (c) Metasurface-enhanced antenna array and its transversal view. (d) Reconstructions of the blood-mimicking target using the antenna with and without metasurface.

ing speed of conventional MWI are often limited. To address these challenges, metamaterials have been integrated into MWI systems, resulting in clearer, faster, and more precise medical images [99]. The potential of metamaterial-aided MWI has been demonstrated in applications such as brain and breast imaging, showing promise for early disease detection [100–102]. For instance, as illustrated in Fig. 5, Razzicchia et al. [87] developed metasurface-integrated antennas for enhancing microwave brain imaging, showing a significant increase in SNR and imaging accuracy for stroke detection. Hossain et al. [103] proposed a textile antenna integrated with frequency-reconfigurable metamaterials, which could adeptly identify early-stage breast cancer in a simulated setting.

3. SIGNAL-BASED CONTACTLESS SENSING

Compared with EM imaging utilizing invisible EM beams to produce images of the human body and its internal tissues, bones, and organs, signal-based EM sensing focuses on quantitatively/qualitatively extracting the impact of human movements on EM waves, and then inferring human motions and status with the extracted variations. Specifically, portable radar and Wi-Fi are two commonly used signal-based EM human sensing schemes. Furthermore, metamaterials have been integrated into the existing signal-based EM sensing approaches to improve system freedom and enhance sensing performance.

3.1. Radar-Based Sensing Technology

Radar technology has exhibited exceptional capabilities in detecting human presence, tracking human movement, and characterizing motion patterns [104, 105]. It can proficiently identify individuals within a designated area by quantifying the influence of the human body on EM signals. Therefore, radar systems can analyze human motion characteristics with high precision, ranging from macroscopic movements of the entire body to nuanced limb movements and even subtle vital signs. Several existing signal-based human sensing systems using radars are listed in Table 4. Next, we will briefly introduce the basic principles of three typical radar systems for signal-based human sensing, followed by an overview of the existing radar-based sensing applications.

3.1.1. Fundamental Principles of Radar-Based Sensing

A. UWB radar operates by emitting very short-duration pulses across a broad frequency spectrum [106]. When these pulses encounter a target, they are reflected to the radar receiver. By measuring the time delay between the transmitted and received pulses, the radar could estimate the radial distance between the radar and the target. The wide bandwidth of UWB signals results in high resolution, enabling the radar to distinguish closely spaced objects. Additionally, UWB signals can penetrate materials like walls and foliage, making it effective for through-the-wall sensing and detecting buried objects.

B. Doppler radar utilizes the Doppler effect to measure the relative velocity of a target [107]. It operates by transmitting a CW signal at a fixed frequency. When the transmitted signal reflects off a moving target, the frequency of the reflected echo shifts proportionally to the target's velocity relative to the radar. Then, the measured frequency shift, known as the Doppler shift, could accurately determine the radial velocity of moving objects.

TABLE 4. Typical Wi-Fi based contactless human sensing systems for B&H applications.

Ref.	Sensing Measurement	Applications	Methodology
[116]	RSS	Human position and tracking	proposing sigma-point Kalman smoothers for RSS -based indoor localization of elderly individuals
[117]	CSI	3D Human Pose Estimation	Constructing a 2D AoA spectrum and utilizing DL to model the relationship between the spectrum and the 3D human skeletons
[118]	CSI	Single-person tracking	Leveraging Doppler frequency shift to separate dynamic human components and then estimating the AoA and distance for tracking
[119]	CSI	Multiperson tracking	Leveraging polarization of WiFi signals to simultan -eously track multiple persons
[120]	CSI	Human respiration sensing	Proposing a respiration tracking technique and a body -tracking technique for sleeping vital-sign sensing
[121]	CSI	Multiperson respiration sensing	Using independent ICA to separate the mixed signal and obtain the separation information of each person
[122]	CSI	Respiration and heartbeat monitoring	extracting CSI phase differences and separating phys -biological signals from the phase difference data
[123]	CSI&RSS	Multiperson activity recognition	Combining CSI and RSS at the feature level for fine-grained multiple-subject human activity recognition.
[124]	CSI&RSS	Human Motion Detection	Constructing a 4-D time-varying vector to train a two-stage ML model for motion detection
[125]	BFM	respiration monitoring and human trajectory tracking	introducing the BFM-ratio to quantitatively extract the impact of human motions on WiFi signals

C. FMCW radar transmits a continuous EM wave whose frequency linearly varies over time, known as a chirp. The fundamental principle involves measuring the time delay and frequency shift between the transmitted and received signals. Specifically, the transmitted chirp signal reflects off a target and returns to the radar with a time delay proportional to the radial distance. Meanwhile, the Doppler effect [107] leads to a frequency shift in the received signal, which can be measured to determine the target's radial velocity. Then, human status and motions could be inferred with the range and radial velocity estimations.

3.1.2. Applications of Radar-Based Sensing

A. Through-the-wall human detection: Due to the capability of penetrating obstacles and providing high-resolution sensing, UWB radar has been widely applied to through-the-wall human detection applications. For example, Zheng et al. [108] proposed a human pose reconstruction system with a UWB MIMO radar, which was capable of perceiving human posture and status through the wall. Meanwhile, Sun et al. [109] developed a Wi-Fi based passive radar system to accurately detect minute human motions like typing and breathing. Furthermore, instead of using radar signal processing algorithms, Zheng et al. [110] proposed a self-attention-empowered DL model, which could directly extract human-related information from radar echoes, and perform various human sensing tasks, e.g., pose estimation and person re-identification.

B. Activity recognition: As a non-intrusive and continuous sensing scheme, radar could monitor human movements and activities without the need for wearable devices, providing great potential for contactless human activity sensing [17]. For example, Erol and Amin [111] proposed a multilinear subspace human activity recognition algorithm by exploiting the underlying dependency and correlations in the three radar signal dimensions, i.e., slow-time, fast-time, and Doppler frequency. Furthermore, Li et al. [112] proposed a semisupervised DL model, which was capable of extracting sufficient human activity information from limited radar micro-Doppler spectrograms and then achieving remarkable human activity recognition performance. Meanwhile, Song et al. [68] proposed a micro-Doppler-based algorithm to estimate human motion directions by using a single-input-single-output UWB impulse radar.

C. Vital-sign sensing: Vital-sign sensing is another critical application of radar technology, particularly in healthcare and medical diagnostics [113, 114]. For example, Zito et al. [115] created a complementary metal-oxide-semiconductor (CMOS) UWB pulse radar sensor for non-contact respiratory rate monitoring, which was effective in tracking sub-centimeter chest movements in adults and infants. Meanwhile, Li et al. [67] developed a non-line-of-sight multipath target searching and position estimating (NLOS-mTSPE) algorithm to process mmWave FMCW radar signals and continuously detect human breathing in non-line-of-sight regions. Furthermore, Mercuri et al. [69] proposed a random body movement rejection algorithm, which can detect human vital signs from the received FMCW radar signals even when the human individual has moderate body random movements.

3.2. Wi-Fi Based Sensing Technology

As a technology that enables wireless internet and network connectivity using radio-frequency (RF) waves, Wi-Fi has been widely utilized to establish connections with a broad array of mobile devices and Internet-of-Things (IoT) gadgets. As a result, the interaction of Wi-Fi signals with the physical surroundings endows Wi-Fi signals with a wealth of environmental information, thus providing a low-cost and ubiquitous environmental sensing scheme [126].

3.2.1. Fundamental Principles of Wi-Fi Based Sensing

Received signal strength (RSS) [116, 123, 124], channel state information (CSI) [117–121], and beamforming feedback matrix (BFM) [125, 127] are commonly utilized measurements for Wi-Fi sensing, which are briefly introduced as follows.

- **RSS** [128]: In Wi-Fi systems, a transmitted signal generally propagates to the receiver through different paths, where the signal experiences reflection, diffraction, and scattering, resulting in a superposition of multipath components. In this case, RSS is adopted to measure the received power at a specific time and employed as a pattern-matching parameter to determine the positions of human targets.
- **CSI** [12]: CSI contains fine-grained amplitude and phase information of the WiFi signal and could capture human movement information at the subcarrier level. Furthermore, the MIMO configuration of Wi-Fi also provides CSI with more spatial diversity. With the spatial and frequency diversity, CSI has higher granularity in recording wireless channel characteristics than RSS, allowing more precise human sensing.
- **BFM** [125]: BFM is a data structure used in wireless communication systems, particularly in MIMO configurations. It contains feedback information from the receiver about the optimal transmission beams or antenna configurations. This feedback helps the transmitter adjust its beamforming strategy, optimizing signal strength, data rates, and overall link performance by focusing the transmission energy in the best direction.

RSS, CSI, and BFM have distinct strengths and weaknesses in WiFi-based human sensing. Specifically, RSS is a coarse-grained metric that provides signal strength measurements but lacks spatial resolution and is highly sensitive to environmental changes, limiting its accuracy in human sensing. CSI offers detailed channel response information, capturing fine-grained motion and vital signs with higher accuracy; however, it requires specialized hardware, complex data processing, and is affected by multipath interference. BFM, commonly used in MIMO beamforming, enhances spatial resolution and robustness against interference, making it effective for precise localization and tracking. However, it is not always readily available on commercial devices and varies across hardware implementations, posing challenges for standardization and large-scale deployment.

3.2.2. Applications of Wi-Fi Based Sensing

Thanks to the low-cost and ubiquitous characteristics, Wi-Fi based human sensing has gained tremendous attention and achieved remarkable advancements in a range of B&H applications.

A. Human pose estimation: The purpose of human pose estimation is to locate key points of the human body in the input data [129]. To this end, Wi-Fi has been employed for pose estimation, which is realized by analyzing the RF signals reflected off the human body with the DL technique [130]. Chen et al. [131] introduced an Evolving Attentive Spatial-Frequency Network (EASFN) to integrate static spatial and dynamic frequency information from CSI measurements for 2D human pose estimation. Furthermore, Ren et al. [117] developed a 3D human pose estimation system *GoPose*, which utilized 2D Angle of Arrival (AoA) spectrum from Wi-Fi reflections and DL to estimate 3D human poses. However, GoPose mainly focused on single-person 3D pose estimation. By contrast, Yan et al. [132] proposed a Transformer-based DL framework to process the CSI data collected from Wi-Fi devices and perform end-to-end multi-person 3D pose estimation.

B. Human tracking: Wireless human localization and tracking is one of the core technologies in the B&H area [118, 133, 134]. For instance, Wang et al. [118] proposed a real-time passive Wi-Fi tracking system *WiDFS* that leverages CSI to track a single person with high precision, overcoming challenges like transceiver asynchronization and multipath interference, without requiring subject-specific training. Furthermore, to achieve multiperson tracking, Venkatnarayan et al. [119] leveraged the polarization diversity to accurately separate and track multiple individuals in real-time, without disrupting the Wi-Fi devices' primary data communication functions. Tan et al. [135] developed a CSI-based multi-user tracking system and extracted the signal reflection of each user with multiple Wi-Fi links and the available Wi-Fi channels at 5 GHz.

C. Vital-sign sensing: Wi-Fi signals could be employed to monitor human vital signs, e.g., respiration and heartbeat, exhibiting substantial utility in B&H applications [136, 137]. For example, Ali et al. [120] utilized the transformations of Wi-Fi signal to analyze and quantify the impact of respiration and body movements, enabling robust sleep vital sign tracking without the need for user-specific calibration. To achieve multiperson vital-sign sensing, Zeng et al. [121] proposed a multi-antenna Wi-Fi system for multiperson respiration sensing and applied Independent Component Analysis (ICA) to separate and recover the detailed respiration patterns of different individuals. Additionally, Yi et al. [125] proposed the BFM-ratio metric to achieve quantitative human motion sensing and demonstrated its effectiveness through theoretical analysis and experiments in applications like respiration monitoring and human trajectory tracking.

3.3. Metamaterial-Based Sensing Technology

3.3.1. Metamaterial in Signal-Based EM Sensing

Although Wi-Fi and radar-based sensing have gained enough achievements, there are still some obstacles hindering performance improvement. For example, the spatial resolution of the off-the-shelf Wi-Fi based and radar-based systems is limited. When there are multiple persons to be perceived, it is difficult for the existing systems to separate the echo signals of different

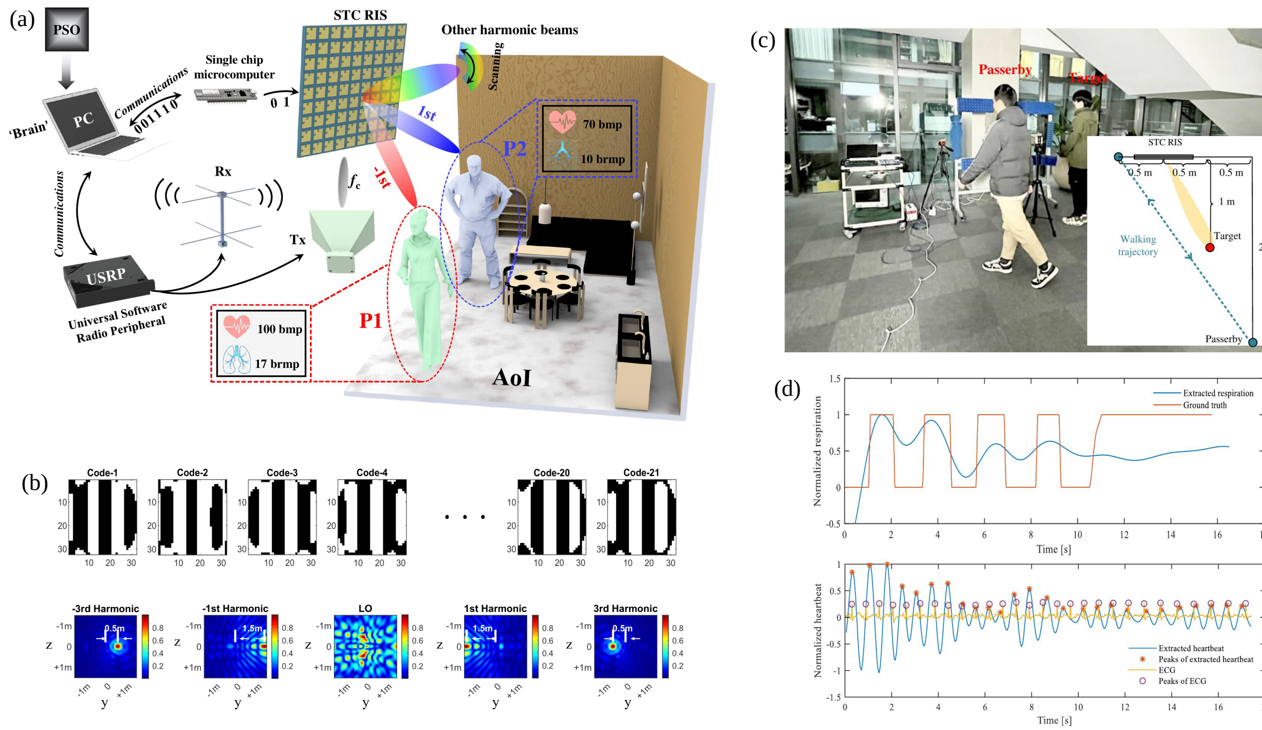


FIGURE 6. Multiperson vital-sign sensing empowered by the STC metasurface [140]. (a) Schematic diagram of the proposed multiperson detection and vital-sign monitoring system. (b) The generated STC coding sequence and the corresponding near-field patterns of four harmonic beams. (c) Experimental setup when a person is passing through the sensing area. (d) The respiration and heartbeat signals are extracted by the proposed sensing system.

persons and perceive their movements simultaneously [138]. Meanwhile, utilizing Wi-Fi signals faces the difficulty of simultaneously achieving wireless communications and sensing functions.

To deal with these challenges, researchers have adopted metamaterials to enhance the performance of signal-based EM sensing, instead of purely optimizing signal processing and detection algorithms. Metamaterial-based sensing leverages the high sensitivity and selectivity characteristics of metamaterials in detecting environmental changes and specific substances, underpinning its applications in the B&H area [25, 139].

3.3.2. Applications of Metamaterial-Based Sensing

A. Medical diagnosis: Metasurfaces offer significant potential for advancing medical diagnosis due to their unique ability to manipulate EM waves with nano-scale precision. Li et al. [141] proposed a metamaterial-based THz biosensor for quick and label-free identification of early-stage cancerous cervical tissue. Two resonant absorption frequencies were employed to identify the ambient change of dielectric properties and then identify the cervical cancerous tissues. Meanwhile, Lin et al. [142] proposed an antibody-modified THz metamaterial biosensor to detect the concentration of carcinoembryonic antigen (CEA). Four metal split-ring-resonators were integrated into a unit cell, whose frequency shift changed linearly with the concentration of the CEA. Furthermore, Upender and Kumar [143] proposed a tunable dual-band THz dielectric-based metamaterial sensor for six different viruses based on their refractive index characteristics.

B. Vital-sign sensing: Due to the flexible manipulation ability of EM waves, metamaterials have also been applied to vital-sign sensing by increasing the spatial resolution and frequency diversity of sensing systems. For instance, Li et al. [144] proposed a metasurface-based health monitoring system, which could simultaneously perceive multiple persons by controlling the spatial distribution of sensing signals. Meanwhile, Xia et al. [145] employed a space-time-coding (STC) metasurface for multiperson breath detection. Harmonic frequencies were generated by the STC metasurface to increase the frequency diversity, and then breath detection was modeled as a blind source separation (BSS) problem. As illustrated in Fig. 6, Li et al. [140] proposed an STC metasurface-based multiperson detection and vital-sign sensing system. Different from *MetaBreath*, the proposed system generated a series of harmonic beams with different frequencies and directions and assigned each person a specific beam for vital-sign sensing.

C. Posture recognition: With large-scale programmable metasurface units, EM sensing systems are endowed with high-resolution sensing ability and thus could achieve precise human posture reconstruction. For instance, Li et al. [4] proposed a human sensing system using a 1-bit programmable metasurface and ML methods, which could recognize human gestures accurately and instantly. Furthermore, Liu et al. [147] proposed an indoor position and human posture recognition sys-

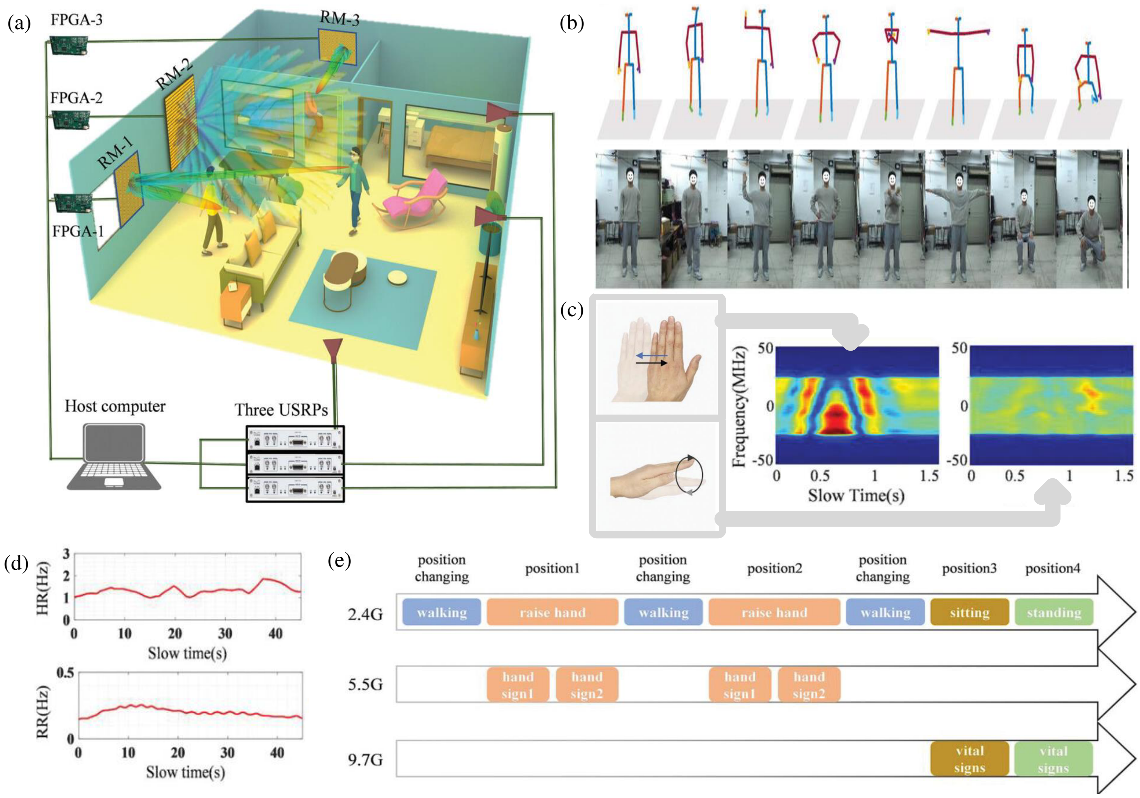


FIGURE 7. Multitask and multiscale human sensing empowered by distributed multi-frequency reprogrammable metasurfaces [146]. (a) System design of the proposed contactless EM human sensing system. (b)–(d) Experiments results of human pose estimation, hand gesture recognition, and vital-sign sensing. (e) Timeline for the three 2.4, 5.5, and 9.7 GHz subsystems, which are utilized for the tasks in (b), (c), and (d), respectively.

tem by integrating a metasurface into an FMCW radar system. A programmable phase shifter with varactor diodes was employed to achieve 360-degree coverage and continuous phase control. Meanwhile, as shown in Fig. 7, Wang et al. [146] proposed an intelligent EM sensing system with distributed multi-frequency reprogrammable metasurfaces. A 2.4 GHz metasurface was adopted for EM wave manipulation, and then the received EM waves were fed into a skeleton-oriented DL network for human pose reconstruction.

4. CONCLUSION

The rapid advancement of contactless EM human sensing technologies has ushered in a new era for biomedical and healthcare monitoring. This review comprehensively surveyed the advancements and applications in contactless EM human sensing, highlighting the significant progress made toward enhancing healthcare and biomedical efficiency. Specifically, we explored two categories of contactless EM human sensing techniques: imaging-based and signal-based ones. Imaging-based contactless sensing, such as medical imaging and radar-based techniques, has demonstrated considerable potential in monitoring vital signs and detecting subtle physiological changes due to its capability of penetrating various materials and producing high-resolution images. However, achieving high imaging resolution imposes more rigorous requirements on equipment. To address these challenges, metamaterials have been employed to adaptively adjust the magnetic field of sensing equipment, thereby enhancing the SNR in imaging. On the other hand, signal-based contactless sensing focuses on extracting the EM properties of human echoes to identify motion and status changes through variations in EM waves. Unlike imaging-based methods, signal-based approaches emphasize the development of signal processing algorithms to accurately extract sensing parameters. As a result, signal-based systems typically require less advanced hardware, making them more cost-effective. Furthermore, metamaterials have been integrated into signal-based sensing to improve noise robustness and enhance overall sensing capabilities. This review has introduced a range of metamaterial-enhanced EM human sensing applications.

Despite these advancements, several critical technical and interdisciplinary challenges remain. The miniaturization of metamaterial is essential for their integration into compact sensing devices, enabling broader adoption in practical healthcare applications. However, achieving high-performance metamaterial with minimal power consumption and material constraints remains a significant hurdle. Additionally, the interpretability of AI-driven sensing models is crucial for ensuring reliability and clinical acceptance. Addressing AI transparency and explainability will be a key to increasing the trust in automated diagnostic and monitoring systems.

Interdisciplinary opportunities, particularly the integration of contactless EM sensing with IoT and 5G, open new possibilities for ubiquitous and real-time health monitoring. The enhanced connectivity provided by these technologies enables seamless data transmission, remote diagnostics, and cloud-based AI processing. However, challenges such as data security, latency, and interoperability with existing medical infrastructures must be addressed to fully realize these benefits.

Future research should focus on developing scalable and cost-effective sensing solutions that seamlessly integrate into healthcare ecosystems. The standardization of data collection protocols and mitigating challenges like signal interference and privacy concerns will be critical for advancing the field. With continuous innovations in metamaterials, AI, and wireless communication, contactless EM human sensing holds immense potential to revolutionize personalized medicine, preventive healthcare, and ubiquitous physiological monitoring.

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