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Wireless Perception-Based Monitoring Technology for Human Vital Signs Status

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Abstract:
With the rapid advancement of 5G communication and computing technologies, wireless sensing has demonstrated extensive application prospects in human vital sign monitoring. This article systematically reviews non-contact vital sign monitoring technologies based on Wi-Fi and millimeter-wave radar, covering their fundamental principles, typical applications, and key challenges. First, the fundamental mechanisms of wireless sensing are introduced, including the use of Channel State Information (CSI) in multipath environments and the micro-Doppler effect in Frequency Modulated Continuous Wave (FMCW) radar. Then, key technologies and developments in typical applications—such as driver behavior recognition, gesture interaction, and heart rate monitoring—are examined in detail. Key challenges in practical applications are summarized, including weak signal detection, clutter suppression, and model generalization. Finally, future development trends are discussed, including multimodal fusion, intelligent algorithm optimization, and device miniaturization. This review aims to provide technical references and insights for future development to researchers in related fields.

Keywords: Wireless perception; vital sign monitoring; millimeter-wave radar; non-contact sensing; deep learning.

1. Introduction

With the rapid advancement of 5G communication and computing technologies, wireless sensing is playing an increasingly vital role in daily life. In contrast to traditional vital sign monitoring methods—which often rely on wearable devices or contact sensors like electrocardiogram (ECG) patches, smart bracelets, or cameras—wireless sensing offers notable advantages including non-contact operation, privacy preservation, and strong anti-interference capabilities [1]. Conventional approaches often face limitations such as poor user experience, long-term wear discomfort, dependence on specific lighting conditions, and potential privacy violations. By leveraging wireless signals like Wi-Fi and millimeter-wave radar, vital sign monitoring can be performed without direct contact, eliminating user discomfort and perceptual burden. Furthermore, these signals can penetrate obstacles

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to enable non-line-of-sight monitoring, demonstrating significant potential in applications such as driving safety, gesture interaction, and healthcare [1]. Recent years have witnessed significant breakthroughs in wireless sensing for applications including behavior recognition, gesture interaction, and heart rate monitoring. This article systematically reviews the fundamental principles and key advances in these typical applications, analyzes current technological challenges, and outlines future directions, thereby providing a valuable reference for researchers in related fields.

2. Wireless Sensing Principle

Wireless sensing technology operates by analyzing how electromagnetic waves interact with the human body and the environment during propagation. The core principle involves detecting subtle changes in signal characteristics—such as amplitude and phase—when signals are reflected, scattered, or diffracted by the human body. By analyzing these variations in received signals, human activities and physiological states can be accurately inferred. Indoor wireless channels are often subject to multipath effects, wherein signals reflect off objects like walls and furniture, creating multiple propagation paths. Human movements or physiological activities modulate the propagation characteristics of these multipath signals, which can be captured via high-resolution Channel State Information (CSI) or radar echo signals at the physical layer. CSI provides amplitude and phase measurements across multiple subcarriers, enabling sensitive detection of environmental dynamics and subtle human movements, thereby facilitating device-free sensing.

Millimeter-wave radar, particularly Frequency Modulated Continuous Wave (FMCW) systems, actively transmits frequency-modulated signals and analyzes reflected waves from humans. Through frequency mixing and Fourier transform, it extracts target distance and velocity information. Periodic micro-movements (e.g., breathing and heartbeat) induce micro-Doppler effects in radar echoes, manifesting as weak periodic modulations in the frequency spectrum. These modulations enable the extraction of vital sign information [2]. The millimeter-wave band's short wavelength (on the order of millimeters) enhances its sensitivity to minute displacements like chest movements during breathing, thereby improving the accuracy of vital sign detection. Additionally, millimeter-wave radar exhibits strong anti-interference capabilities and reliable all-weather operation. Coupled with recent advances in highly integrated millimeter-wave chips (e.g., Texas Instruments' IWR series), it supports device miniaturization and embedded applications.

In summary, wireless sensing leverages the micro-Doppler effects captured via Wi-Fi CSI and millimeter-wave radar, combined with advanced signal processing and machine learning algorithms, to enable effective non-contact monitoring of human behavior and vital signs.

3. Overview of Typical Applications

3.1 Driver Behavior Recognition

Figure 1 illustrates the overall framework of a driving behavior recognition method based on FMCW radar and deep learning.

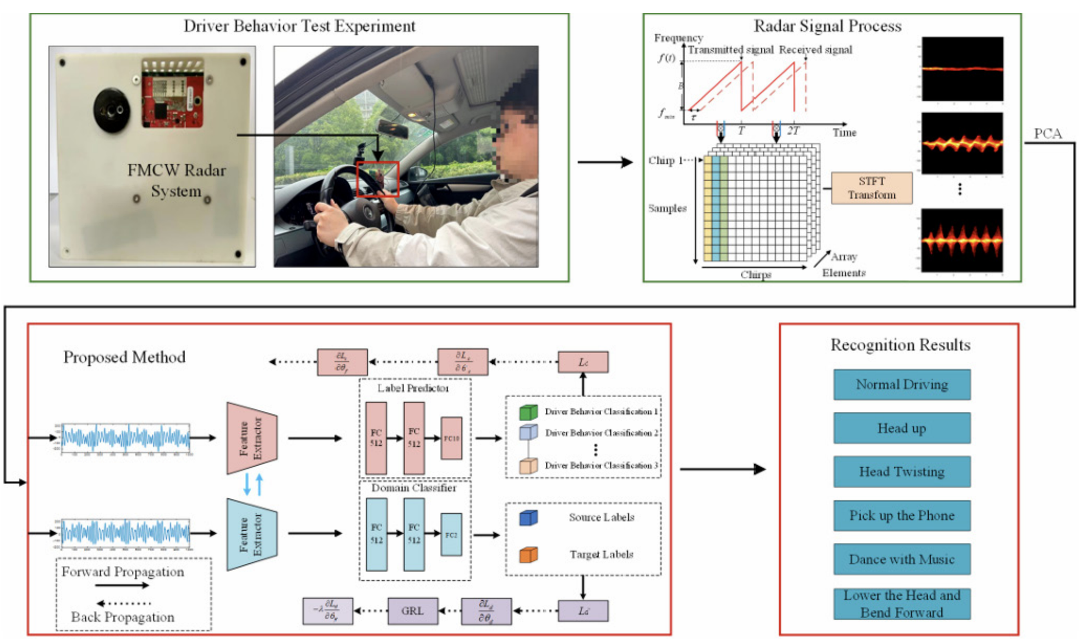

Fig. 1 Schematic diagram of a wireless perception driver behavior monitoring system [3]

Millimeter-wave radar is placed inside the car to monitor the micro-movements of the driver's chest and head. After signal processing, time-frequency features are extracted and input into a deep learning model to recognize driving behavior. The right side displays the differences in radar time-frequency maps corresponding to different driving actions (normal driving, looking up, turning, making phone calls, following music rhythm, and leaning forward).

Vehicle driving safety represents a key application scenario for wireless sensing technology. Unsafe driving behaviors—including fatigue, distraction, and mobile phone use—are major causes of traffic accidents, creating an urgent need for real-time and reliable monitoring solutions. Conventional approaches typically employ in-car cameras to monitor facial expressions and movements, or steering wheel-mounted sensors to detect operational behaviors. However, vision-based solutions are sensitive to lighting conditions and raise privacy concerns, while physical sensors cannot directly capture the driver's physiological state [4, 5]. Millimeter-wave radar offers unique advantages for driver monitoring due to its non-contact operation, strong penetration capability, and strong environmental robustness [6]. Radar systems can be installed on dashboards or other interior surfaces, emitting waves that cover the driver's upper body region. By analyzing micro-movements including chest motions and head movements, driving behaviors can be accurately classified.

Recent advances in deep learning have significantly enhanced the accuracy and generalization capability of driving behavior recognition systems [7]. Chen et al. proposed a multi-scale convolutional long short-term memory network (MCT-CNN-LSTM) incorporating domain adversarial training to improve cross-scenario generalization [3]. This approach employs CNN for time-frequency feature extraction, LSTM for temporal dependency modeling, and attention mechanisms to enhance critical information channels. Adversarial training is further applied to reduce feature distribution discrepancies across different domains. Experimental results demonstrate that this method achieves a behavior classification accuracy of 97.3% on cross-driver and cross-scenario datasets [3]. This demonstrates that through multi-scale feature extraction and domain adaptation, millimeter-wave radar can accurately identify dangerous behaviors (e.g., head nodding, looking sideways, and phone use), effectively addressing the generalization limitations of traditional approaches [3, 8]. The real-time capability and reliability of wireless sensing make it a valuable component of advanced driver-assistance systems (ADAS), enhancing driving safety.

3.2 Gesture Recognition

Gesture recognition, as a key application of wireless perception in human-computer interaction, has been widely deployed in domains including drone control, smart homes, and virtual reality [9]. Compared to macroscopic behaviors, gestures typically exhibit smaller amplitudes and shorter durations, posing challenges such as weak signal variation, brief action spans, and high noise interference. In research, gestures are commonly categorized into static gestures, dynamic coarse-grained gestures, and dynamic fine-grained gestures, based on amplitude and temporal continuity. Each category exhibits distinct signal characteristics: for instance, large arm movements induce significant Doppler shifts, whereas subtle finger motions cause only minor perturbations in the CSI phase.

To enhance recognition performance, researchers have developed strategies including multi-scale feature extraction, multimodal fusion, and advanced preprocessing. Multi-scale spatiotemporal networks (e.g., TSN and TSM) process CSI sequences by fusing local features across segments to capture both long- and short-term dependencies [10]. Multimodal approaches integrate Wi-Fi amplitude and phase, radar, and visual data to enhance signal robustness; high-resolution time-frequency analysis—e.g., short-time Fourier transform (STFT) and wavelet transform—facilitates the extraction of short-duration weak features.

Existing methods have demonstrated significant progress on public benchmarks such as Widar3D, D-ConGR, and SHREC'22. Multimodal fusion models achieve over 90% overall accuracy in recognizing both static and dynamic gestures, with recognition rates for subtle actions improving by more than 20% compared to baseline methods. With further integration of deep learning and signal processing techniques, wireless gesture recognition is poised to play an increasingly important role in applications such as intelligent cockpits and virtual interaction systems.

3.3 Electrocardiogram Generation and Cardiac Monitoring

Non-invasive monitoring of cardiac activity—including heart rate measurement and electrocardiogram (ECG) reconstruction—represents one of the most challenging tasks in wireless vital sign monitoring. Traditional ECG requires electrode contact to acquire electrical signals, whereas wireless approaches indirectly infer cardiac activity by capturing mechanical chest vibrations, enabling contactless continuous monitoring. Early wireless heart rate monitoring primarily utilized radar or Wi-Fi to extract respiratory and cardiac cycles, deriving metrics such as heart rate and heart rate variability (HRV) [11]. However, parameters like heart rate alone are insufficient to compre-

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hensively characterize cardiac health status.

Recent studies have attempted to reconstruct ECG waveforms from radar echoes by leveraging chest wall micro-vibrations induced by cardiac activity, establishing a mapping between mechanical vibrations and electrical signals to generate synthetic ECG waveforms [12-14]. Current radar-based ECG reconstruction methods predominantly employ deep generative models. However, conventional generative models often exhibit limited performance when handling abnormal rhythms such as arrhythmias (e.g., atrial fibrillation).

To address this limitation, Zhao et al. proposed the AirECG system, which employs low-cost 24 GHz millimeter-wave radar to capture chest vibrations and converts radar signals into ECG via a cross-domain diffusion model [15]. The model learns cross-domain mapping through iterative denoising, incorporates a hierarchical Transformer to fuse local waveform and global rhythm features, and introduces prior correction during denoising to enhance waveform consistency. Experimental results demonstrate that AirECG generates high-fidelity ECG waveforms in both healthy subjects and those with arrhythmias, achieving a correlation coefficient exceeding 0.92 with standard lead ECG and an atrial fibrillation detection accuracy of 98.8%. Furthermore, integrating multimodal data (e.g., from fiber optic sensing) could enhance system robustness and advance wireless ECG monitoring toward medical-grade home applications.

4. Technical Difficulties and Challenges

Despite its significant potential, practical applications of wireless sensing face several key challenges. Weak signal detection remains challenging as vital sign-induced signal variations are easily obscured by environmental noise, including airflow disturbances and irrelevant human movements. This necessitates the development of high-sensitivity detection algorithms. Clutter suppression represents another core challenge. Both static background reflections and dynamic interference can mask target micro-motion signals. Common mitigation approaches include high-pass filtering, principal component analysis (PCA), and multi-sensor fusion to enhance signal-to-noise ratio (SNR) and system robustness.

Limited model generalization capability restricts cross-scenario deployment. Variations in user physiognomy, posture, and environmental layouts cause significant distribution shifts in channel characteristics. Although transfer learning and domain adaptation methods (e.g., Domain-Adversarial Neural Networks, DANN) help mitigate this issue, model performance in unseen scenarios remains unstable. Real-time processing requirements and computational complexity present additional constraints. Many deep learning models incur substantial computational overhead, hindering real-time implementation on resource-constrained embedded platforms. Thus, model compression techniques and efficient algorithms are required for optimization.

Multi-target monitoring presents difficulties due to signal overlapping, which complicates individual separation. Existing research explores array antenna beamforming, MIMO technology, and deep learning clustering for multi-target detection, though these approaches remain in preliminary stages. Additionally, data privacy and security concerns require attention. Although wireless sensing does not capture visual images directly, it may inadvertently reveal users' health status and behavioral patterns. Protective measures including end-to-end encryption, localized data processing, and compliance-based authorization mechanisms need implementation.

5. Development Trends and Prospects

Future advancements in wireless sensing for human vital sign monitoring are expected to evolve along several key directions:

Wireless vital sign monitoring will advance through multimodal fusion, intelligent algorithms, hardware miniaturization, standardization, and enhanced privacy protection. Multimodal fusion compensates for limitations of single-mode sensing by integrating data from Wi-Fi, radar, infrared, and other sensors, thereby enhancing system comprehensiveness and accuracy. Integrated sensing and communication (ISAC), as envisioned for 6G systems, will further facilitate infrastructure reuse and enable seamless wide-area monitoring.

Regarding intelligent algorithms, self-supervised learning, federated learning, and reinforcement learning will enhance model adaptability in data-scarce and edge-computing scenarios, while dedicated network architectures incorporating physical priors will improve signal representation efficiency. At the hardware level, continued miniaturization and cost reduction of millimeter-wave radar and Wi-Fi front-ends will promote their integration into automotive systems, smart home devices, and wearable terminals.

Standardization efforts will promote the establishment of public datasets, evaluation benchmarks, and unified protocols, facilitating technology comparison and industrial adoption. Privacy protection requires strengthening at both algorithmic and system levels through techniques such as differential privacy and encrypted computation, along with developing regulatory frameworks to provide institutional safeguards for technology deployment.

In summary, key development directions for wireless vital sign monitoring technology include multimodal fusion, intelligent algorithms, miniaturized hardware, and security-compliance. These advancements are anticipated to enhance system performance and reliability, broaden application scope, and address current bottleneck challenges.

6. Conclusion

This article systematically reviews recent research progress and future directions in human vital sign monitoring using wireless perception technologies. Wireless sensing leverages channel characteristic variations resulting from interactions between wireless signals and the human body to enable non-contact physiological state perception, demonstrating significant advantages in applications including driving safety, human-computer interaction, and cardiac activity monitoring. The article elaborates on the fundamental principles of CSI and FMCW radar, summarizes advanced methodologies in behavior recognition, gesture interaction, and ECG reconstruction, analyzes key technical challenges including weak signal detection, environmental interference, model generalization, and real-time processing constraints, and outlines promising future research directions including multimodal fusion, intelligent algorithms, and standardization efforts.

With continued interdisciplinary innovations, wireless sensing technology is poised to play an increasingly vital role in domains such as intelligent transportation, home healthcare, and human-computer interaction, providing core technological support for enhancing quality of life and health outcomes.

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