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Analysis of Wireless Vital Sign Detection Method

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Abstract. As technology advances and living standards improve, people's awareness of vital signs monitoring is gradually increasing. Meanwhile, the potential of wireless sensing technology in this field has become increasingly evident. Wireless sensing technology can efficiently monitor the health status of individuals by analyzing changes in wireless signals. This article highlights four typical wireless sensing vital signs monitoring technologies. By employing methods such as Fresnel zone modeling, intelligent reflective surface (IRS) optimization, and a multi-module system framework, these technologies are applied practically. The article concludes that the RSSI model has high accuracy for single-person detection in fixed scenarios but is sensitive to the environment and location. The CSI combined with the IRS model enhances robustness through dynamic beamforming, and improves multi-user separation accuracy, but comes with higher hardware costs. The article aims to deepen the understanding of wireless sensing vital signs monitoring and to provide theoretical support and technical analysis for the advancement of wireless sensing in this field.

Keywords: Wireless sensing, WiFi signal, breathing detection, heart rate detection.

1. Introduction

As society develops, people's concern for health and well-being is growing, leading to a rising demand for vital signs monitoring [1,2]. Consequently, wireless sensing devices with autonomous detection capabilities are gaining more attention. Wireless sensing technology can efficiently monitor the health status of individuals by analyzing changes in wireless signals. Compared to traditional sensors, wireless sensing systems can achieve non-intrusive detection, which not only protects privacy but also reduces deployment costs [3,4]. With the continuous advancement of wireless sensing technology, it has seen significant growth in areas such as smart homes, intelligent care, and security alerts, injecting vitality into the future of digital living.

In the context of home health monitoring, traditional methods for breathing and heart rate monitoring primarily rely on contact sensors or cameras, which come with numerous inconveniences and limitations. Contact sensors can affect sleep quality due to discomfort, while camera monitoring poses risks of privacy breaches [5]. Therefore, it is crucial to develop a new technology that can monitor vital signs without physical contact [6]. The wireless sensing life detection system offers a novel solution. Wireless sensing technology not only enables non-invasive vital sign monitoring but also prevents privacy leaks during the process. Additionally, this

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technology has minimal interference from obstacles, enhancing the device's resistance to interference.

This article aims to explore wireless sensing technology, presenting several models of wireless sensing technology. It analyzes and compares specific technologies, highlighting their advantages and disadvantages, and offers suggestions for improving the less favorable aspects. Additionally, the article discusses the practical applications of wireless sensing in various scenarios, providing a reference for the widespread adoption of wireless sensing technology in society. This further enhances the broad application of wireless sensing technology. To promote the gradual improvement of medical standards, the comprehensive development of personal care technology, and the concept of public health, the article makes corresponding contributions.

2. Typical technology comparison and analysis

To study the wireless sensing vital signs technology in more detail, this section focuses on comparing and analyzing the Person-in-WiFi 3D model, the CSI model based on respiratory monitoring, the respiratory monitoring system based on WiFi RSSI, and the BreatheBand system framework.

2.1. Person-in-WiFi 3D model

The Person-in-WiFi 3D model has evolved from the original 2D model into a 3D structure, enhancing spatial perception. However, this evolution has also introduced several issues, such as network convergence, an excessive number of parameters, slow training speeds, and higher latency. The lack of an end-to-end processing flow has led to significant error accumulation. Therefore, this Person-in-WiFi 3D model is based on.

The Transformer and DETR have been improved, with improved overall accuracy and stability compared to the original version. The Person-in-WiFi 3D model consists of three important modules: WiFi encoder, attitude decoder and fine decoder.

(1) The WiFi encoder divides the WiFi signal into blocks and discretizes it into tokens, extracts global spatio-temporal context information, and provides rich feature representation for subsequent decoding.

(2) The pose decoder interacts with the encoder features through a randomly initialized multi-query mechanism to predict the position of 3D joint points. Global attention is used instead of local convolution to avoid the limitations of traditional hierarchical feature extraction. The multi-query mechanism enhances the ability to capture diversity and uncertainty.

(3) The fine decoder optimizes the initial prediction results based on the attention mechanism, corrects the deviation caused by signal noise and environmental interference, and further improves the accuracy.

In general, Person-in-WiFi 3D achieves efficient and accurate estimation of 3D human posture from WiFi signals through the encoder of Transformer architecture and PhaseFi phase denoising technology, solves the bottleneck of convergence, efficiency and accuracy of traditional 3D networks, and provides a new end-to-end solution for wireless perception field.

2.2. CSI model based on respiratory monitoring

The CSI model based on respiratory detection perceives [2] by analyzing the phase and amplitude changes of the multi-path propagation of WiFi signals. Its technical principle is to use the dynamic

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path modulation signal caused by chest movement and optimize the wave.

The formation of a bundle enhances the integration of respiratory components with intelligent reflective surfaces (IRS). This model offers non-contact, low-cost, multi-user robustness, and privacy protection, and can accurately restore the respiratory characteristics for identity verification. However, it has limitations such as single-target detection, sensitivity to motion interference, strong environmental dependence, and high computational complexity. The improvement plan includes using MultiSense for multi-user detection, employing blind source signal separation to suppress motion interference based on the low-frequency rhythm characteristics of Wi-Sleep, dynamically adjusting the configuration of the IRS in real-time through the Fresnel model, and utilizing the LSTM network from WiReader. The network achieves algorithm lightweighting [5] to enhance real-time performance and scalability.

2.3. Breathing monitoring system based on WiFi RSSI

The RSSI model for respiratory detection employs the Fresnel zone blade diffraction model to analyze the quantitative relationship between the received signal strength indicator (RSSI) and the quantified displacement of the human thoracic cavity, thereby detecting breathing [7-9]. The technical principle is as follows: the human respiratory process is modeled as the periodic motion of a flat cylinder. The relationship between the diffraction gain and thoracic displacement is quantified using the Fresnel ratio (μ). When the human body is near the boundary of the Fresnel zone ($\mu \geq -0.577$), the periodic changes in path loss caused by breathing can be extracted from the RSSI using the Fast Fourier Transform (FFT) to determine the respiratory rate. The advantages of this model include: ① non-contact detection, reducing costs by using commercial WiFi devices; ② high accuracy for single-person detection at fixed positions, with an accuracy rate of 93.8% for respiratory rate estimation in good positions; ③ strong resistance to sleep posture interference, capable of detecting in various postures such as lying on the back or side. The disadvantages are: ① dependence on the human position, requiring it to be near the boundary of the Fresnel zone, where slight movement can significantly reduce accuracy; ② limited to single-target detection, unable to separate multiple signals; ③ significant impact from environmental multipath interference, making the signal easily drowned out by noise in complex scenarios; ④ inability to penetrate obstacles, making it unsuitable for wall-separated scenarios. By adjusting the height of the transceiver or the human position to ensure the Fresnel ratio is within the effective range (-0.577,1), and using FFT combined with bandpass filtering (0.1~0.5Hz) to enhance the respiratory signal, the stability of single-person detection in fixed scenarios is improved.

2.4. BreatheBand system framework

The BreatheBand system comprises five main modules: data acquisition, data preprocessing, indoor personnel detection, respiratory feature extraction, and the generation of respiratory sequences [10]. This system boasts high precision, operates without physical contact, is cost-effective, and demonstrates robust performance with strong privacy protection. However, it has limitations such as single-target detection, interference from movement, environmental dependency, and complex computational requirements. To address these issues, MultiSense's Blind Source Signal Separation (BSS) technology can be utilized, leveraging the independence of signals in the time-frequency domain for independent component analysis

The (ICA) or tensor decomposition algorithm is used to decompose the mixed [11] multi-person breathing signals into independent source signals. The BSS algorithm is applied to the CSI data of

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each subcarrier to achieve multi-user breathing signal separation. For motion interference, anti-motion optimization can be implemented, such as using Wi-Sleep to distinguish between breathing and movement by leveraging low-frequency rhythm characteristics. For environmental dependency, environmental adaptation can be performed, with environmental modeling based on the Fresnel zone model to analyze the impact of obstacles on multipath propagation. Additionally, improvements have been made to computational complexity, with the WiReader system's LSTM network architecture replacing the original genetic algorithm and HMM training with a lightweight deep learning model [8]. The Long-Short Memory Network (LSTM) [4] is used to directly process the time series features of CSI data, reducing intermediate complex transformations and lowering computational load.

3. Applicationsscenarios

3.1. Case 1: Intelligent Reflective Surface (IRS) respiratory monitoring model based on CSI

The model optimizes the channel state information (CSI) of WiFi signals using intelligent reflector surfaces (IRS), aiming to enhance the accuracy of respiratory detection. The technical approach primarily involves three aspects: First, it employs dynamic modeling of Fresnel zones, combined with real-time environmental scanning by a depth camera. This model analyzes the impact of obstacles on signal multipath propagation, dynamically adjusting the phase codebook of the IRS to prioritize subcarriers with less interference. Second, the model introduces a lightweight LSTM algorithm, replacing traditional genetic algorithms with long short-term memory (LSTM) networks. This network directly learns the temporal features of CSI sequences and reduces latency through edge computing, effectively addressing the computational complexity of traditional algorithms. Finally, in multi-user scenarios, the model incorporates blind source separation (BSS) technology, using independent component analysis (ICA) to decompose mixed signals [10], thereby achieving the separation of multiple respiratory signals. In terms of performance, the model achieves a single-person respiratory rate error of less than 0.1bpm in laboratory settings, with waveform similarity to commercial breathalyzers exceeding 90%, demonstrating significant improvements in accuracy. Additionally, by utilizing IRS beamforming technology, the intensity of respiratory signals is increased by 30% when subjects are in non-face-to-face positions such as lying on their side or facing away, achieving a detection accuracy rate of 94.3%. However, the model has certain limitations, primarily due to its reliance on real-time modeling by a depth camera, which leads to higher hardware costs; and in multi-user scenarios, the complexity of the signal separation algorithm still needs further optimization

3.2. Case 2: Fresnel zone blade diffraction model based on RSSI

The model is based on the Received Signal Strength Indicator (RSSI) and uses the Fresnel zone blade diffraction model to quantify the path loss changes caused by breathing. The technology primarily addresses two aspects: First, it models the human thoracic movement as a [7]-periodic displacement of a flat cylinder using respiratory modeling, defining the Fresnel gap (μ) to describe the relationship between human position and signal diffraction gain. When $\mu \geq -0.577$, the RSSI fluctuations caused by breathing can be extracted through the Fast Fourier Transform (FFT). Second, it performs bandpass filtering and position optimization, enhancing the respiratory frequency band signal through a bandpass filter (0.1~0.5Hz) and adjusting the height of the transmitter and receiver to ensure that the human body is within the effective range of the Fresnel

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zone (-0.577,1). In terms of performance, in good laboratory positions (e.g., $\mu = -0.5$), the accuracy of respiratory rate estimation reaches 93.8%, with errors under postures such as supine and lateral lying all being less than 5%. However, the model has some limitations, such as sensitivity to human position; slight movements (such as a translation of 0.5 meters) can cause the μ to deviate from the effective range, reducing the accuracy to 74.5%; it cannot handle multiple people or wall-separated scenarios.

3.3. Case 3: BreatheBand system framework

Te technology achieves respiratory monitoring through a five-module architecture: First, the CSI tool is used for data acquisition and preprocessing to obtain WiFi signals. These signals are then downsampled to 20Hz using the Savitzky-Golay filter and phase correction is applied to eliminate time-varying offsets. Next, respiratory features are extracted, and the Respiratory Energy Ratio (RER) is used to filter out low-frequency (0.1667-0.6167Hz) features. Independent Component Analysis (ICA) is employed to separate the respiratory signal from motion interference. Then, sequence generation and optimization are performed using a Gaussian-Hidden Markov Model (MCG-HMM) to generate respiratory waveforms. The state sequence is optimized using the Viterbi algorithm. In terms of model performance, it can adapt to various scenarios, including complex environments such as offices and bedrooms. For stationary subjects, the error in respiratory rate is 0.2 bpm, while for movement scenarios (such as slight walking), the error increases to 1.5 bpm. Additionally, privacy protection is ensured by non-visual perception solutions that avoid the privacy risks associated with cameras, meeting the safety requirements of medical settings. However, there are certain limitations, such as the single-target design, which can lead to error accumulation when multiple people are monitored simultaneously due to signal mixing; the high computational complexity limits real-time processing to 30-second segments.

4. Challenges

Currently, obstacles in indoor complex environments, such as walls, furniture, and moving human bodies, significantly alter the wireless signal propagation path, leading to RSSI/CSI signals containing a significant amount of static multipath noise and dynamic interference. For instance, the Fresnel zone model based on RSSI requires the human body to be in a specific position (Fresnel gap \mu \geq-0.577). If the position shifts or the environmental layout changes, the detection accuracy can drop sharply from 93.8% to below 70%. Most existing technologies are designed for single targets. When multiple people are present simultaneously, breathing signals can overlap at the receiving end. Traditional blind source separation algorithms, such as Independent Component Analysis (ICA), have high computational complexity and struggle to handle real-time multi-user dynamic interaction scenarios. For example, in scenarios with more than three people, the BreatheBand system experiences breathing rate errors exceeding 2 bpm due to signal mixing. Additionally, non-breathing movements of the human body, such as walking and waving, generate signals with frequencies (0.5-5Hz) that partially overlap with the low-frequency characteristics (0.1-0.5Hz) of breathing. Traditional band-pass filtering or LSTM models struggle to fully suppress high-frequency interference, and the detection error can increase to 1.8 bpm in motion scenarios. Finally, high-precision solutions, such as IRS + depth cameras, require additional hardware, making home deployment costs exceed 1,000 yuan. Low-cost solutions, such as pure RSSI models, require only commercial WiFi devices but have a limited detection range (typically <3 meters) and cannot penetrate obstacles.

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In the future, self-supervised learning and federated learning can be introduced to train general models using vast amounts of unlabeled WiFi signals, addressing the challenge of cross-environment generalization. For instance, by employing contrastive learning, the model can automatically distinguish between 'breathing fluctuations' and 'environmental noise,' maintaining an accuracy rate of over 90% in unfamiliar environments. Additionally, it is recommended to integrate 6G terahertz communication with intelligent metasurfaces (RIS) to create a wireless sensing system with seamless coverage.

To achieve breath monitoring across walls and multi-floor synchronous perception, the Knowledge Network utilizes dynamic modeling of Fresnel zones. This allows for the reconstruction of breathing waveforms through signal diffraction features, even when the target is in an adjacent room. 3. Low-cost hardware ecosystem: Develop WiFi 6E/7 chips with integrated phase correction modules, leveraging high bandwidth (such as 320MHz channels) to enhance resolution. These chips are compatible with traditional RSSI/CSI protocols, enabling consumer-grade devices like smart routers to integrate breath monitoring functions at a cost of less than 500 yuan. 4. Medical-grade application expansion: Deeply integrate with medical IoT (IoMT) to develop a comprehensive system for 'breathing anomaly warning-remote diagnosis-rehabilitation tracking.' For instance, if a pause lasting more than 10 seconds or abnormal rapid or slow breathing (over 30bpm or under 8bpm) is detected, the system automatically triggers cloud-based medical platforms to intervene, generating personalized health recommendations based on historical data.

5. Conclusion

This paper explores non-contact respiratory monitoring technology based on WiFi signals, employing methods such as Fresnel zone modeling, Intelligent Reflective Surface (IRS) optimization, and a multi-module system framework. It analyzes the application of different models based on the Received Signal Strength Indicator (RSSI) and Channel State Information (CSI) in respiratory monitoring. The study finds that the RSSI model achieves an accuracy rate of 93.8% for single-person detection in fixed environments, but it is sensitive to environmental and positional factors. By integrating the CSI with the IRS model, dynamic beamforming enhances robustness in multi-posture detection, achieving a separation accuracy rate of 94.5% for multiple users, although this approach incurs higher hardware costs. Current technologies still face challenges in separating multiple target signals, suppressing motion interference, and reducing hardware costs.

Future research could focus on multimodal fusion (such as WiFi and millimeter-wave radar), optimizing generalization through self-supervised learning, and developing low-power WiFi chips that integrate Inertial Navigation System (IRS). This research offers a non-contact, highly private breathing monitoring solution for smart healthcare, advancing WiFi technology towards 'communication-sensing integration.' It is significant for home health management and 6G pervasive sensing.

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