Research on Vital Signs Monitoring Technology Based on Wireless Sensing

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Abstract. Vital signs monitoring serves as a critical means of assessing human health, yet traditional contact-based devices suffer from issues such as poor comfort and potential allergenicity. Contactless monitoring technology utilising Wi-Fi signals has emerged as a significant avenue for overcoming these limitations, owing to its widespread availability, penetration capabilities, and low-cost advantages. This paper systematically investigates core methodologies, application scenarios, and technical bottlenecks of wireless sensing technologies for respiratory and heart rate monitoring. The study first compares two primary respiratory monitoring techniques: CSI complex-domain signal processing and CSI ratio trajectory analysis. It also examines two key heart rate monitoring approaches: end-to-end CNN learning and rotary projection combined with HSR subcarrier selection. Results indicate that the current optimal solution achieves respiratory errors below 0.5 BPM and median heart rate errors of 0.8 BPM in static scenarios, significantly outperforming baseline methods. The study further explores the technology's suitability across four key application domains—medical monitoring, sleep assessment, home-based elderly care, and in-vehicle safety—validating its cross-scenario potential. Existing bottlenecks are identified as environmental interference, insufficient dynamic robustness, individual variability, and multi-object separation challenges. Future breakthroughs require collaborative efforts in multimodal sensor fusion, lightweight algorithms, and clinical integration. This technology pioneers a new paradigm for contactless, continuous, and all-scenario vital signs monitoring, extending health management beyond clinical settings into daily life and laying the technological foundation for building a proactive health society.

Keywords: Wireless Sensing; CSI; Vital Signs Monitoring; Respiration and Heart Rate Estimation.

1. Introduction

Vital signs serve as critical indicators for assessing fundamental human physiological functions, playing an irreplaceable role in health monitoring, disease diagnosis, and emergency care. Among these, respiration and heart rate are the most pivotal dynamic metrics, underpinning normal life activities while providing real-time reflections of an individual's health status. While traditional contact-based monitoring devices offer high-precision respiratory signals, they suffer from poor comfort and may cause skin irritation with prolonged wear. Consequently, developing non-contact monitoring technologies to extract respiratory and heart rate signals has become paramount to enhance monitoring comfort and convenience. Wi-Fi signals, owing to their ubiquity, penetration capabilities, and low-cost advantages, present an ideal medium for achieving imperceptible monitoring. Channel State Information (CSI), as the physical layer channel characteristic data of Wi-Fi, can capture minute vibrations induced by respiration and heartbeat. Human thoracic movements modulate the signal propagation path, causing periodic variations in CSI amplitude and phase, thereby providing the theoretical foundation for monitoring.

The significance of wireless respiratory and heart rate sensing research lies in pioneering a new paradigm for contactless, continuous, and full-time-domain vital signs monitoring. This extends health surveillance beyond discrete medical settings to encompass all-encompassing life scenarios such as sleep, home environments, and travel. Systems for respiratory and heart rate detection developed using wireless sensing technology enable long-term, non-contact monitoring of breathing and heart rate within indoor environments. This facilitates continuous observation of individuals' physical health, thereby laying the technological groundwork for precision medicine and proactive health societies.

Recent years have witnessed significant advancements in wireless sensing technology globally. Wang Jianjun achieved synchronous tracking of multiple patients' respiration/heartbeat in hospital settings using the 90–300 GHz sub-terahertz band and beamforming techniques, with an error rate below 5% when penetrating clothing [1]. Samir Mosleh proposed the PhaseBeat (based on discrete wavelet transform) and TensorBeat (based on tensor decomposition) algorithms, leveraging CSI phase difference data to enhance interference resistance. This achieved high-precision respiration/heartbeat monitoring using commercial WiFi devices for the first time, with an error rate ≤5% in dynamic scenarios [2]. Zhang Yuan introduced a millimetre-wave-CSI fusion solution (24GHz band), combining AI algorithms to achieve 99% accuracy in static heart rate/respiration monitoring—significantly surpassing industry standards [3].

This paper investigates wireless perception-based vital signs monitoring technology, conducting comparative analyses of representative techniques for respiration and heart rate monitoring. It systematically examines specific application scenarios for wireless perception in vital signs monitoring, summarises existing challenges and technical bottlenecks, and outlines future research directions. The primary research content is reflected in the following three aspects.

First, two representative technologies for respiration and heart rate monitoring are examined through systematic comparative analysis to identify their respective strengths and limitations. Subsequently, the applicability and suitability of wireless perception-based vital signs monitoring technologies within practical scenarios are evaluated. Finally, the research findings are summarised, current technical bottlenecks and challenges are analysed, and future research directions are proposed.

2. Core Technical Method Comparisons

2.1 Respiratory Monitoring Technologies

2.1.1 CSI Complex-Domain Signal Processing

Li Siteng proposed an innovative method for simultaneously calibrating both amplitude and phase distortions in Channel State Information (CSI) [4]. This technique utilises WiFi CSI to estimate the respiratory rate of individuals within indoor environments. The core approach significantly enhances the accuracy and robustness of respiratory rate monitoring by addressing CSI amplitude and phase distortion issues, combined with time-domain analysis.

The core innovation lies in employing time-domain channel impulse response (CIR) analysis rather than mainstream frequency-domain approaches. Conventional methods focus on frequency-domain CSI characterisation but remain susceptible to multipath channel interference. This paper employs inverse discrete Fourier transform (IDFT) to convert CSI into CIR, thereby directly extracting time-delay components (e.g., thoracic displacement) associated with respiratory motion. This time-domain focused strategy enables more precise separation of respiratory signals while circumventing frequency-domain noise interference.

To eliminate amplitude and phase distortions caused by measurement errors, the literature proposes a dual calibration mechanism for CSI calibration. This method preserves true phase information, avoiding signal loss associated with independent amplitude-phase processing.

The calibrated complex CSI or CIR is employed for respiratory rate detection, utilising a Band of Interest (BoI) scoring method to select sensitive subcarriers or time-delay components. Scoring is based on Power Spectrum Density (PSD). Ultimately, the PSD detection method identifies PSD peaks within the 0.2–0.5 Hz frequency band as respiratory rate estimates, circumventing the noise sensitivity issues inherent in traditional peak detection.

This approach demonstrates high monitoring accuracy, with 86% of respiratory rate estimation errors below 0.5 BPM in public dataset tests. It exhibits stable performance within the 0.2–0.5 Hz respiratory range and insensitivity to positional changes, proving its robustness.

The drawbacks include reliance on multi-antenna MIMO systems for phase differential support, entailing higher hardware costs. Furthermore, WiFi bandwidth limitations (40 MHz) impose constraints on time-domain resolution, adversely affecting multipath separation efficacy.

2.1.2 CSI Ratio Trajectory Analysis Method

Wei Zhuang proposed an innovative respiratory monitoring approach by tracking the dynamic trajectory of CSI ratios on the complex plane [5]. Respiratory monitoring is achieved by tracing the movement of dual-link CSI ratios across the I/Q complex plane. Traditional methods relying on CSI amplitude or phase are susceptible to motion interference, leading to inaccurate cycle counting. This approach calculates the CSI ratio across both links. This ratio eliminates carrier frequency offset and packet detection delay noise, transforming respiratory signals into dynamic trajectories on the complex plane. The core discovery: significant inflection points appear in the trajectory during exhalation/inhalation transitions, enabling precise respiratory cycle localisation.

Regarding key technological breakthroughs, a dispersion model is proposed to mark points of significant motion interference. The dispersion of trajectory samples within a computational time window is calculated. Gaussian process regression is employed for non-uniform sampling interpolation, utilising radial basis functions (RBF) as the kernel function. Trajectories are fitted using spline curves to identify inflection points corresponding to respiratory transitions. An algorithm for respiratory segment extraction is designed, reconstructing respiratory waveforms based on changes in trajectory path length.

The method's advantages include an average error rate (AER) below 0.35 bpm during static conditions, an average accuracy (ACC) exceeding 93%, and the ability to utilise commercially available WiFi equipment for monitoring, offering low-cost and easy deployment. Static signal removal and the dispersion model significantly reduce interference from environmental static objects and large human movements, enhancing monitoring accuracy.

A limitation of this approach is its sensitivity to subject movement; sustained physical activity such as turning over or walking, substantially reduces monitoring precision. Furthermore, the method involves steps including Gaussian regression and curve fitting, necessitating consideration of computational complexity.

2.2 Heart Rate Monitoring Techniques

2.2.1 End-to-End Learning with CNNs

Hassan Ali Sorgon proposed a human activity and emotion recognition system based on WiFi channel state information (CSI) mechanisms, utilising machine learning algorithms for modelling [6].

The research innovatively utilises the reflective properties of Wi-Fi Channel State Information (CSI) for heart rate monitoring. The hardware configuration comprises two ESP32-WROOM-32U development boards, functioning as transmitter and receiver respectively, positioned at a fixed 3-metre distance. CSI data is collected via the ESP CSI toolkit, forming a complex matrix that captures characteristics of signal propagation including amplitude attenuation, phase shift, and multipath effects. The raw CSI data undergoes three critical preprocessing steps: noise reduction, matrix reshaping, and normalisation. This process leverages the spatial geometric information within CSI to map wireless signal reflection characteristics onto patterns of human heart rate variation.

A dedicated convolutional neural network was designed to achieve end-to-end heart rate estimation. The model was trained using synchronously annotated data (GT) from smartwatches, with Adam algorithm parameter updates to prevent overfitting in the validation set. By analysing signal disturbances caused by blood volume changes, the model achieved a 96% test accuracy rate.

The method's advantages include: - Avoiding manual feature engineering through automatic extraction of effective features; - Claimed high accuracy of 96%; - Reduced deployment costs via inexpensive IoT devices.

The method's limitations include its status as a black-box model, resulting in poor interpretability and difficulty analysing failure cases; strong data dependency requiring substantial annotated data for CNN training; and a lack of validation in dynamic scenarios, with testing confined to static conditions.

2.2.2 Rotational Projection + HSR Subcarrier Selection Technique

Sun Junchong proposed an innovative non-contact heart rate monitoring method based on Wi-Fi channel state information (CSI) [7]. This approach employs rotational projection technology to integrate both amplitude and phase information from CSI signals, thereby overcoming the limitations of traditional single-dimensional analysis.

The research designed a CSI ratio model and rotational projection to compute the CSI ratio for dual-receiver antennas, eliminating carrier frequency offset (CFO) and phase noise. On the complex plane, the real part (I) and imaginary part (Q) were linearly combined at angle θ to generate a candidate signal set, enhancing heartbeat characteristics. Concurrently, a Savitzky-Golay filter with an adjustable window size was employed to smooth the signal while preserving waveform features.

The study innovatively proposes the Heartbeat Sub-Component Ratio (HSR) metric to achieve precise subcarrier selection. This quantifies the ratio of primary to secondary energy peaks within the heartbeat frequency band (0.8–2.5 Hz), where higher values indicate greater heartbeat sensitivity. The five subcarrier peak frequencies are integrated using normalised HSR values as weights.

This method offers robust interference resistance, with the HSR metric effectively suppressing noise to enhance the signal-to-noise ratio. It achieves high precision, with a median error of 0.8 bpm—a 20% improvement over existing techniques—and demonstrates strong environmental robustness, maintaining accuracy >96.5% in both conference room and dormitory settings.

The method's drawbacks include computational complexity, with low real-time performance for rotation projection and wavelet decomposition requiring high-performance equipment; significant distance limitations, where errors rise markedly to 2.5 bpm beyond 3 metres; and demanding hardware requirements necessitating custom Wi-Fi devices.

3. System Analysis and Application Research

3.1 Non-contact Monitoring

The vital signs monitoring system employs non-contact, passive sensing technology to collect real-time health data without wearable devices, adapting to diverse living environments. Yao Ge noted that such systems capture cough frequency and respiratory distress patterns non-invasively (e.g., the Wi-COVID system), providing early symptom screening for isolation wards and substantially reducing healthcare worker infection risks [8]. For chronic disease patients, this technology achieves groundbreaking long-term, unobtrusive home monitoring: heart failure patients receive 72-hour advance warnings of acute episodes through resting heart rate fluctuation trends, while COPD patients gain dynamic respiratory function tracking without cumbersome equipment. These applications integrate seamlessly into daily living environments, utilising standard routers as hardware foundations to reduce medical-grade monitoring costs to under $50, achieving seamless coverage from individual health management to public health protection.

3.2 Sleep Quality Assessment

Sleep health monitoring applications focus on prolonged, undisturbed sleep apnoea surveillance and sleep quality assessment, enhancing user sleep experiences and promoting healthy living. Guo Lingchao proposed achieving continuous health management through non-invasive monitoring methods [9]. In domestic settings, wireless-sensing sleep monitoring systems can track sleep stages, postural changes, and vital signs in real time, providing individuals with quantified sleep quality reports. This technology overcomes the temporal and spatial constraints of traditional clinical monitoring, enabling chronic disease patients (such as those at high risk for hypertension or diabetes) to receive early warnings for risks like apnoea or abnormal limb movements during natural sleep, facilitating timely intervention.

3.3 Remote Care Systems

Home/elderly care health monitoring systems deliver daily health management and remote supervision services for the elderly or patients, with anomaly alerts ensuring timely responses to safeguard safety. Zavall Hussein proposed an innovative method based on WiFi signal-derived emergency semantic feature vector extraction, deeply applying it to real-time monitoring of critical health events in home-based elderly care scenarios[10]. This technology leverages existing ambient WiFi signals to deliver non-contact, wearable-free, round-the-clock discreet monitoring. It maximises respect for elderly privacy and lifestyle habits while eliminating discomfort from wearable devices and charging concerns, significantly enhancing user compliance and feasibility for home-based elderly care monitoring.

3.4 Real-time Driver Condition Monitoring

Vehicle-mounted Wi-Fi enables monitoring of a driver's heart rate and respiration to identify fatigue or sudden illness. Zheng Tianyue's V2iFi system employs compact radio-frequency sensing technology to achieve real-time, non-invasive monitoring of critical driver vital signs in actual driving conditions, significantly enhancing driving safety and health management capabilities.[11] This system employs commercial pulse radio equipment mounted on the vehicle windscreen to capture and analyse metrics such as respiratory rate, heart rate, and heart rate variability in real time, enabling early detection of potential fatigue-related driving risks. For instance, when a driver's respiratory rate decreases or heart rate variability becomes abnormal due to prolonged driving, the system issues timely alerts to prevent fatigue-induced traffic accidents.

4. Technical Bottlenecks and Breakthrough Directions

4.1 Environmental Interference

Wireless sensing technology faces significant environmental interference challenges during practical deployment. These interferences primarily originate from three sources.

Firstly, environmental noise and the movement of unrelated individuals. The movement and activities of other persons within the monitoring area generate complex reflections and variations in wireless signals. These non-target signals significantly contaminate the vital signs signals of the target subject, making it difficult to accurately extract faint breathing or heartbeat signals.

Secondly, noise from the devices themselves and neighbouring wireless equipment. The Wi-Fi routers and FMCW/UWB radar modules employed inherently generate hardware noise. Concurrently, other operational Wi-Fi networks, Bluetooth devices, microwave ovens, and similar equipment within the environment produce radio frequency interference that can overwhelm the target signal.

Finally, complex multipath effects come into play. Indoor environments are filled with reflective surfaces, causing wireless signals to reach the receiver via multiple paths, resulting in multipath propagation. These multipath signals superimpose and interfere with one another, distorting or blurring the signal characteristics carrying vital signs information.

Addressing these interferences necessitates developing more robust signal processing algorithms, such as advanced adaptive filtering techniques, environmental awareness mechanisms, and leveraging artificial intelligence to model environmental noise and implement effective suppression.

4.2 Robustness Challenges

System robustness is the core challenge determining reliable operation in real-world scenarios. Complex environments refer to settings beyond ideal laboratory conditions.

When subjects are not stationary but engaged in daily activities (such as light movement, housework, or turning over), significant bodily motion can mask subtle thoracic excitations or skin vibration signals, making it difficult for existing algorithms to distinguish vital signs from motion noise.

Movement of objects within the monitoring area (e.g., opening/closing doors, moving chairs), fluctuations in ambient temperature and humidity, and even airflow (e.g., from fans or air conditioning) may introduce unpredictable signal variations.

When the target is partially obstructed by walls, furniture, or other objects, signal attenuation becomes severe and propagation paths complex, causing a sharp decline in signal-to-noise ratio and significantly reducing monitoring accuracy.

Enhancing system robustness requires developing algorithms capable of stable operation across diverse postures and activity states. This includes integrating posture recognition and motion compensation techniques to isolate vital signs, alongside designing models with greater adaptability to occlusion and signal attenuation.

4.3 Consideration of Individual Variability

Individual variation is a critical variable affecting the accuracy of wireless vital signs monitoring. Individuals differing in height, weight, and body fat percentage exhibit significant variations in thoracic movement amplitude and skin properties regarding wireless signal reflection/penetration. For those with a heavier build, signals penetrate deeper while thoracic movement amplitude is relatively smaller, potentially making accurate capture more challenging.

The subject's posture (e.g., sitting, lying, side-lying, curled up) alters the orientation, distance, and propagation path of the target area (thorax, body surface) relative to the signal source, thereby affecting signal strength and characteristics.

The distance between the target and the signal source/receiver directly impacts signal strength. As distance increases, signal attenuation occurs, the signal-to-noise ratio decreases, and detection accuracy typically diminishes (e.g., certain technologies explicitly exhibit significantly increased error beyond 3 metres).

Even for the same individual, the thickness and material of clothing covering the body (particularly those containing metallic components), or objects such as thin blankets or books between the subject and the device, can attenuate or distort signals, increasing the difficulty of extracting vital signs information.

Algorithm design must fully account for modelling and compensating these factors, such as through adaptive calibration mechanisms that adjust parameters based on body type and distance, or by utilising multimodal information to assist in posture and occlusion assessment.

4.4 Challenges in Multi-Target Recognition

Significant technical challenges arise in scenarios requiring simultaneous vital signs monitoring of multiple individuals within the same space (e.g., multi-person households, hospital wards).

Vital sign signals (breathing, heartbeat) from multiple subjects and environmental reflection signals become intermingled at the receiving end. The core challenge lies in effectively separating these mixed signals and accurately associating the separated signals with their corresponding individuals. This distinction becomes particularly difficult when subjects share similar physical characteristics (body type) or are positioned close together.

The physiological signal frequencies of multiple subjects may be close or overlapping (such as similar respiratory rates or heart rates), leading to frequency domain aliasing that obscures the precise identification of individual frequencies.

Real-time separation and tracking of signals from multiple subjects necessitates more sophisticated algorithms (such as advanced blind source separation techniques, spatial filtering like beamforming, and target tracking algorithms). This places higher demands on the computational capabilities of edge devices, potentially leading to processing delays or increased system power consumption.

Addressing multi-target monitoring necessitates integrating spatial positioning technologies (for precise individual location), enhanced signal processing capabilities (such as spatial filtering using multi-antenna arrays), and efficient machine learning models to distinguish and track each individual's physiological characteristics.

5. Conclusion

This study systematically explores vital signs monitoring technology based on wireless perception, with core achievements summarised in three aspects.

Firstly, technological evolution breakthroughs. In respiratory monitoring, CSI complex-domain signal processing and CSI ratio trajectory analysis significantly enhanced respiratory rate detection accuracy (error ≤0.5 BPM), achieving substantial progress in environmental interference resistance (static object occlusion, NLOS scenarios). For heart rate monitoring, innovative techniques such as rotating projection fusion of amplitude-phase information and HSR subcarrier selection, combined with end-to-end CNN learning, achieved a median error of 0.8 bpm in static scenarios (a 20% improvement over baseline), resolving the challenge of extracting physiological features under weak signal conditions.

Secondly, comprehensive application validation spans four key scenarios: medical monitoring, sleep surveillance, home-based elderly care, and vehicle safety. This demonstrates the technology's universal applicability and societal value across complex environments.

The third point concerns the identification of core bottlenecks. Existing challenges are concentrated across four dimensions: environmental interference, robustness challenges, individual variations, and multi-object separation. Interdisciplinary collaborative research is urgently required to address these issues.

To overcome existing technical limitations, subsequent research will concentrate on four key directions. The first direction is multimodal perception fusion. Integrating data from diverse sensors such as radar and infrared can enhance monitoring stability in complex environments (e.g., multi-person scenarios, strong interference). The second direction is lightweight algorithm development. By designing more streamlined AI models, compatibility with everyday devices like smartphones and wristbands can be achieved, enabling low-power real-time monitoring. The third direction is individual adaptive optimisation. This involves developing automatic calibration techniques to mitigate the effects of body size and posture variations, thereby extending the effective monitoring range (3-5 metres). The fourth direction is medical scenario implementation. Collaborating with hospitals to establish pathological databases will facilitate the integration of this technology into clinical monitoring systems, with the aim of securing medical certification.

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