Transactions on Computer Science and Intelligent Systems Research
ISSN: 2960-1800, eISSN: 2960-2238 | Volume 11
TPCEE 2025

Research and Application Analysis of Heart Rate Monitoring Technology Based on CSI

Xingtong Ou *

Department of Electronic Information and Automation, School of Tianjin University of Science and Technology, Tianjing, China

* Corresponding Author Email: ouxingtong72@gmail.com

Abstract. Chronic diseases affecting younger people have become prevalent in contemporary society. Among chronic diseases, cardiovascular and cerebrovascular diseases are predominant, with countless people dying from cardiovascular diseases each year. Long-term heart rate variability (HRV) monitoring can warn of arrhythmia, myocardial ischemia, and other conditions, reducing the mortality rate from acute events by 30%. The advent of non-contact detection technology has made long-term monitoring possible. This paper reviews heart rate monitoring technologies based on channel state information (CSI), discusses techniques such as CSI phase difference, rotation projection, and discrete wavelet transform, and examines their current applications in medical and other fields, to provide new technical insights for cardiovascular health management. It also points out that existing technologies generally suffer from high computational complexity and susceptibility to complex environmental influences. In the future, we hope to combine intelligent technology to enhance environmental adaptability and quickly realize the transition of CSI heart rate monitoring from clinical applications to full-scene applications.

Keywords: CSI; Non-contact; Heart rate monitoring.

1. Introduction

Cardiovascular disease is one of the major health threats worldwide. According to statistics from the World Health Organization (WHO), approximately 18.6 million people die from cardiovascular disease each year. Heart rate variability (HRV) is an important indicator of cardiovascular health, and its long-term monitoring is significant for the early warning of arrhythmia, myocardial ischemia, and other diseases. Traditional heart rate monitoring methods, such as electrocardiography (ECG) and photoplethysmography (PPG) monitoring, have certain limitations. Therefore, there is an urgent need to develop a non-contact, long-term, stable heart rate monitoring technology.

In recent years, non-contact heart rate monitoring technology based on CSI has gradually emerged. Its non-contact nature not only avoids the drawbacks of traditional contact devices but also improves patient compliance, making it particularly suitable for monitoring patients who require long-term observation [1-4]. In addition, CSI technology can achieve a monitoring accuracy of less than 3% within a distance of 5 meters and has been clinically validated. With the continuous advancement of technology, CSI heart rate monitoring technology is expected to play an important role in cardiovascular health management.

The development history of CSI-based heart rate monitoring technology can be traced back to the early 2010s. With the widespread popularity of Wi-Fi devices and the convenience of wireless sensing technology, research on Wi-Fi-based passive sensing has developed rapidly. These studies typically focus on the received signal strength indicator (RSSI) or CSI. Compared to RSSI, CSI is more difficult to obtain but provides finer-grained perception capabilities [5]. In 2016, Hao Wang introduced the concept of Fresnel zones in his paper and used the amplitude information of CSI to detect breathing [6]. In 2017, Xuyu Wang proposed a method in his thesis that uses the CSI corresponding to the RF signals received by two receiving antennas to capture respiratory characteristics through phase difference changes. These studies laid the foundation for subsequent CSI-based heart rate monitoring technologies [6].

In recent years, significant progress has been made in Wi-Fi-based heart rate monitoring technology. For example, Wang et al. captured key point signals from the human body using Wi-Fi devices, enabling human visualization without visual devices [5]. In addition, Wang et al. demonstrated how to steal smartphone passwords using commercial Wi-Fi devices [1]. These studies indicate that WiFi sensing technology has broad application prospects in daily life and work, and opens up new possibilities for the future development of wireless sensing technology.

In the field of heart rate monitoring, most studies tend to choose the amplitude or phase of the CSI signal for detection, which ignores the complementarity of amplitude and phase in CSI signals for vital sign detection [5]. Although some studies have considered the complementarity of amplitude and phase, in actual solution design, they still only select one of the amplitude or phase signals that provides superior perception performance. This selective method may not fully utilize the information content of the CSI signal, thereby limiting further improvements in heartbeat detection accuracy.

In summary, CSI-based heart rate monitoring technology has undergone a process of gradual maturation from initial exploration. With continuous technological advances and expanded application scenarios, this technology is expected to play an even greater role in the future.

This paper summarizes recent innovations in CSI technology for heart rate monitoring and compares and analyzes these technologies. Tracing the development of these technologies provides direction for future research. First, Section 2 briefly explains the basic CSI technology and technical principles required to implement heart rate monitoring, providing a theoretical foundation for the rest of the paper. In Section 3, the application of CSI technology in heart rate monitoring is systematically summarized. Three typical technologies—discrete wavelet transform, rotated projection, and CSI phase difference—are primarily listed, and detailed comparative analyses of the performance, advantages, and disadvantages of different technologies are provided to serve as a reference for practical applications. Section 4 discusses the application of CSI heart rate monitoring technology in postoperative rehabilitation, chronic disease management, smart homes, and other scenarios, demonstrating its broad application prospects.

2. Basic Theory

The principle of wireless signal sensing is primarily based on the interaction between wireless signals and the environment or target objects. By analyzing the signal changes generated by these interactions, information about the environment or target objects can be obtained.

Wi-Fi's ability to detect vital signs stems from the fact that breathing and heartbeats cause deformation of the abdomen and chest, which in turn affects the propagation of Wi-Fi signals. CSI captures these changes, enabling the recovery of the required vital signs. CSI provides detailed, fine-grained physical information about how signals propagate from the transmitter to the receiver, including detailed amplitude and phase information for different subcarriers, which can be obtained from several off-the-shelf WiFi NICs, such as the Intel WiFi Link 5300 NIC and the Atheros AR9580 chipset [6-8]. In addition, CSI indicates the amplitude and phase information of the subcarrier level measurement of the OFDM channel. It is a more stable representation of channel characteristics than RSS. However, due to large phase fluctuations in noise and time and frequency desynchronization between the transmitter and receiver, the phase information collected from CSI data cannot be directly used for life monitoring. Figure 1 shows the general process of converting CSI data into the required heart rate monitoring signal.

Figure 1. Flowchart of heart rate monitoring based on CSI

3. Typical Technologies

3.1. CSI Phase Difference

In the field of wireless communications, CSI refers to the channel attributes of the communication link. The CSI phase is more sensitive to the environment than the CSI amplitude, so subtle changes in the channel environment can be measured using the CSI phase. However, errors may be introduced due to the influence of the transceiver hardware equipment. Within the same data packet, these errors have a relatively fixed impact on different subcarriers, mainly introducing linear errors and bias. CSI phase error correction is critical for accurate channel state measurement. Xuyu Wang extracts stable phase differences through linear transformations (such as carrier frequency offset (CFO) and sampling frequency offset (SFO) removal) and hardware-assisted calibration (multi-antenna phase difference elimination of unknown offset $\Delta\beta$), and uses them for heart rate signal monitoring [9].

Unlike previous studies, this method does not select the amplitude commonly used in the past as the signal selection, but instead selects the phase difference for analysis. Since each antenna used to transmit signals has the same clock and frequency, the phase difference data of CSI is stable after subtracting the randomness of the original phase in the WiFi NIC. At the same time, thanks to the different distances and directions between the transmitter and receiver, the CSI phase difference and amplitude-based methods are more robust, further reducing signal attenuation.

From the results, it can be seen that phase is sensitive to small displacements (such as 0.1–0.5 cm chest movements caused by breathing) and is superior to amplitude data. The calibrated phase difference has bounded variance in a static environment and performs well in multi-person scenarios.

Combined with angle estimation (5 GHz WiFi) and deep learning, it has higher applicability in complex indoor environments.

In addition, this technology also has some shortcomings. It relies on specific network cards (such as Intel 5300 NIC) to obtain raw CSI data, and calibration requires auxiliary hardware (such as signal distributors). Furthermore, AOA estimation errors increase significantly (by approximately 6°) in NLOS environments, and dynamic interference (such as human movement) can easily cause signal abnormalities. At the same time, real-time processing requires high-performance computing (such as tensor decomposition and deep learning), but edge device deployment is limited. The phase calibration algorithms (such as CP decomposition and adaptive filtering) on which the calculations depend are complex to optimize and require re-modeling when affected by environmental changes.

3.2. Rotary Projection

Previous studies typically only considered using a single amplitude or phase difference. However, Juncong Sun, Xin Bian, and Mingqi Li et al. used rotational projection to linearly combine the real part (I) and imaginary part (Q) of the CSI ratio on the same complex plane at discrete angles θ ranging from 0 to 2π [1]. By scanning the angles, all possible weights of I/Q are exhausted in one go, generating a set of complementary candidate signals, from which the waveform with the most obvious heartbeat characteristics is selected, combining amplitude and phase difference. When performing CSI measurements on a single antenna, phase information itself is not suitable for monitoring due to time-varying random phase offsets. However, by using the ratio of CSI, stable phase difference information between two antennas can be obtained (because random phase offsets are canceled out). This integrates the phase and amplitude information of the CSI ratio, overcoming monitoring blind spots and thereby expanding the perception range. This method was inspired by the projection method used for respiratory detection and extended to heartbeat detection [10].

As shown in Figure 2, it is important to note that complex numbers can be represented in the form of bi and Aeiθ, where a and b represent the real part (I) and imaginary part (Q), respectively, while A and θ represent the amplitude and phase. The real part (I component) and imaginary part (Q component) of the CSI ratio exhibit complete complementarity, meaning that if the I component at a particular location is unsuitable for heartbeat monitoring, the Q component may be advantageous, and vice versa. Therefore, combining these two components effectively unifies the monitoring of amplitude and phase. By assigning different weights to the composite, I and Q components, a series of candidate combinations of subcarrier signals can be generated. The designed subcarrier selection sensor method is then used to filter out the subcarrier signals most suitable for heartbeat monitoring for further analysis.

Rotational projection can effectively enhance signal perception, suppress noise interference, highlight heartbeat characteristics in signals, and reduce interference from irrelevant noise. This method makes full use of phase and amplitude information, overcoming the limitations of traditional methods that rely solely on a single signal component. Rotational projection allows signal perception to be optimized by adjusting the projection angle, offering great flexibility and adaptability to different signal characteristics and application scenarios.

At the same time, rotational projection requires multiple projections and analyses of signals, resulting in a large amount of computation and a relatively complex processing process. This computational complexity can increase significantly when processing high-sampling-rate signals, which can adversely affect the real-time performance and efficiency of the system. The effectiveness of this method depends on the choice of projection angle. If the projection angle is not chosen appropriately, it may not be possible to fully utilize its advantages, and it may even lead to the loss or misinterpretation of signal characteristics. Since rotary projection requires the processing of complex signals and involves complex mathematical calculations, it places high demands on the computing power and precision of the hardware.

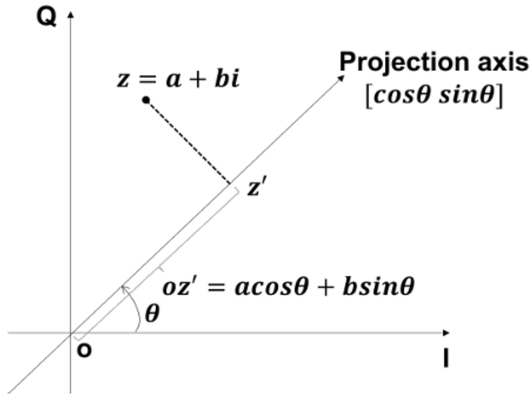

Figure 2. Principal diagram of rotational projection

3.3. Rotary Projection

When processing heartbeat signals, Hou Xiaoqing selected the Coiflet 4 wavelet basis function, which has good correlation with the output signal, as the wavelet decomposition function [11]. The discrete wavelet transform (DWT) decomposes the CSI heartbeat signal into two layers of multiscale decomposition using the Coiflet 4 basis function, generating approximation and detail coefficients. Subsequently, the median-estimated soft threshold is used to remove noise, and then the clean QRS waveform is reconstructed through inverse transformation.

After this process is completed, the wavelet decomposition reconstruction process retains the coefficients of the useful signal and reduces most of the noise coefficients to zero, thereby completing signal denoising [7]. The denoising process can be roughly divided into three parts, as shown in Figure 3.

Figure 3. DWT processing flow chart

After denoising, the signal obtained has relatively little noise. The characteristics of the Q, R, and S waves are relatively obvious, among which the R wave has the largest amplitude, the most obvious characteristics, and is the easiest to identify. Therefore, first locate the R peak, then locate the remaining waveforms, and use a series of algorithms to obtain the required QRS waveform diagram, which is the common heart rate diagram.

Compared with short-time Fourier transform (STFT) and continuous wavelet transform (CWT), DWT can adaptively adjust the window according to frequency, efficiently remove baseline drift and power frequency interference, while completely retaining key features such as R-peak changes.

DWT can provide signal features at different resolutions, making it very effective in processing signals with multi-scale features. It performs excellently in signal denoising. By selecting appropriate wavelet basis functions and thresholding, noise can be effectively removed from the signal while retaining its main features. Moreover, its computational complexity is relatively low, especially when compared to the continuous wavelet transform (CWT). By utilizing discrete wavelet basis functions and fast algorithms (such as the Mallat algorithm) for signal decomposition and reconstruction, it achieves high computational efficiency in practical applications. After being embedded in the WiFi-CSI system, DWT successfully achieved contactless heart rate extraction. Compared with the MIT-BIH Arrhythmia Database, the R-peak recognition accuracy reached 99.66%, which can be promoted to real-time health monitoring scenarios such as homes and nursing homes.

When processing signals, DWT may be affected by boundary effects. Boundary effects refer to errors in the results of wavelet transforms caused by signal discontinuity at the boundaries of signals. At the same time, the performance of DWT depends largely on the choice of wavelet basis functions.

Different wavelet basis functions have different effects on signal decomposition and reconstruction, so it is necessary to select the appropriate wavelet basis functions according to the specific application scenario. Although the computational complexity of DWT is relatively low, the amount of computation is still large when processing large-scale data.

4. Application Analysis

4.1. Postoperative Rehabilitation Monitoring

Non-contact heart rate monitoring technology has significant application value in postoperative rehabilitation monitoring. For example, during the rehabilitation process for burn patients, traditional electrode patches may cause secondary damage to the wound. By monitoring heart rate variability (HRV) non-invasively and combining it with an AI wound management system, the healing process can be assessed. The Shenzhen Third People's Hospital and Southern University of Science and Technology team are currently conducting related research [12], which is expected to be put into clinical practice for testing in the future.

4.2. Chronic Disease Home Management

Patients with chronic diseases require long-term heart rate monitoring to manage their conditions. The non-contact cardiac monitoring system developed by the University of Science and Technology of China enables completely non-contact lifelong monitoring and supports the evaluation of radiofrequency ablation surgery outcomes [13]. Meanwhile, Lin Yiqun et al. combined CSI heart rate monitoring technology with respiratory monitoring to provide more comprehensive protection of vital signs [14].

4.3. Smart Home

In the field of smart homes, CSI heart rate monitoring technology can be integrated into smart devices to provide users with health monitoring services. For example, the "Smart Aging" project in Changning District, Shanghai, installed monitoring terminals for 2,000 patients with high blood pressure, resulting in a 31% decrease in emergency room visits. This demonstrates that CSI heart rate monitoring technology has significant advantages in improving the quality of life for the elderly.

5. Conclusion

This paper compares and analyzes three methods: CSI phase difference, rotation projection, and discrete wavelet transform. It finds that there are still some issues that need to be improved, including high computational complexity, excessive reliance on parameter selection, and inaccurate edge feature extraction. In response to the above issues, the following development directions are proposed: To address the issue of high computational complexity, consider optimizing algorithms and introducing parallel computing technology to reduce the complexity of rotation projection and SI phase difference data processing, thereby meeting the requirements of real-time signal processing and big data analysis. Secondly, developing intelligent algorithms based on machine learning to automatically select rotation projection angles and DWT wavelet basis functions can improve the accuracy and reliability of signal processing, thereby reducing dependence on parameter selection. At the same time, research has advanced boundary expansion techniques to reduce DWT boundary effect errors, improve feature extraction accuracy, and further improve data accuracy. Furthermore, developing adaptive signal enhancement and anti-interference algorithms, simplifying antenna calibration and environmental detection, improving the stability and reliability of CSI heart rate monitoring technology in complex environments, and making it applicable to various scenarios. Finally, add algorithms and update databases to ensure the accuracy of data analysis results and enable more comprehensive analysis of health conditions.

In the future, CSI heart rate monitoring technology will rely on multimodal fusion and standardization breakthroughs to achieve large-scale application from laboratories to all scenarios. Through continuous technological innovation and application expansion, CSI heart rate monitoring technology is expected to play a greater role in cardiovascular health management and contribute to global health.

References

[1] Lim S, Jang G S, Song W, et al. non-contact vital signs monitoring of a patient lying on a surgical bed using beamforming FMCW radar [J]. Sensors, 2022, 22(21): 8167.

[2] Khanam F T Z, Perera A G, Al-Naji A, et al. non-contact automatic vital signs monitoring of infants in a neonatal intensive care unit based on neural networks [J]. Journal of Imaging, 2021, 7 (8): 122.

[3] Yang X, et al. A low-complexity non-contact vital sign detection system and heartbeat extraction algorithm [J]. Journal of Physics: Conference Series, 2023, 2477 (1): 012100.

[4] FMCW-based contactless heart rate monitoring [J]. Scientific Reports, 2025, 15 (1): 2616.

[5] Sun J, Bian X, Li M. Non-contact heart rate monitoring method based on Wi-Fi CSI signal [J]. Sensors, 2024, 24 (7): 2111.

[6] Wang H, Zhang D, Ma J, et al. Extracting multi-person respiration from entangled RF signals [J]. Journal of Radar.

[7] Halperin D, Hu W J, Sheth A, et al. Predictable 802.11 packet delivery from wireless channel measurements [C]//Proceedings of the ACM SIGCOMM 2010 Conference. New Delhi, India, 2010: 159 - 170.

[8] Xie Y, Li Z, Li M. Precise power delay profiling with commodity WiFi [C]//Proceedings of the 21st Annual International Conference on Mobile Computing and Networking. Paris, France, 2015: 53 - 64.

[9] Wang X. RF Sensing for Internet of Things: When Machine Learning Meets Channel State Information [D]. 2018.

[10] Zeng Y, Wu D, Xiong J, et al. FarSense: Pushing the range limit of WiFi-based respiration sensing with CSI ratio of two antennas [J]. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 2019, 3 (3): 1 - 26.

[11] Hou Xiaoqing. A study on methods for extracting vital signs based on CSI signals [D]. China University of Mining and Technology, 2020.

[12] Wang H, et al. Toward Camera-PRV-Based Early Warning in Hospital ICU: A Pilot Study [J]. IEEE Internet of Things Journal, 2025, 12 (14): 28623 - 28638.

[13] Zhang B B, Zhang D, Li Y, et al. Monitoring long-term cardiac activity with contactless radio frequency signals [J]. Nature Communications, 2024, 15: 10598.

[14] Lin Yiquan, Qiu Jiefan, Zhang Jinhong, et al. A method for expanding the monitoring range of WiFi breathing monitoring in dynamic scenarios [J]. Journal of Computer Research and Development, 2025, 62 (4): 1075 - 1089.