

Article

# A study of millimeter-wave communication in remote biomechanical monitoring

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**Abstract:** Millimeter-wave communication technology offers high precision, low latency, and non-contact measurement advantages in remote biomechanical monitoring. This study develops a millimeter-wave radar-based monitoring system for precise detection of movement trajectory, heart rate, respiration, and muscle activity. By integrating Short-Time Fourier Transform (STFT), Doppler analysis, and deep learning, the system enhances signal processing and enables multi-parameter fusion analysis. The results support applications in smart medicine, remote rehabilitation, and sports science, advancing millimeter-wave communication in biomechanical monitoring.

**Keywords:** millimeter wave communication; biomechanical monitoring; multiparameter fusion

## 1. Introduction

Millimeter-wave communication technology, characterized by high-frequency bandwidth and low latency, holds significant potential in remote biomechanical monitoring. Traditional monitoring methods rely on contact sensors, which may cause discomfort and are susceptible to environmental interference. In contrast, millimeter-wave radar enables non-contact, long-range, and high-precision monitoring, enhancing the accuracy and stability of physiological parameter detection [1]. This study explores the application of millimeter-wave communication in biomechanical monitoring by constructing a radar-based system and optimizing monitoring accuracy through signal processing, feature extraction, and multi-parameter fusion analysis. The system's performance is assessed in movement tracking, heart rate and respiration monitoring, as well as muscle activity and joint mechanics analysis. The findings contribute to advancing millimeter-wave technology in smart medicine, sports rehabilitation, and health monitoring, offering technical support for precision medicine.

The remainder of the paper is organized as follows: Section 2 discusses the fundamentals of millimeter-wave communication; Section 3 introduces the system architecture and key technologies; Section 4 presents experimental design and evaluation; and Section 5 concludes with findings and future research directions.

## 2. Overview of millimeter wave communication technology

### 2.1. Millimeter-wave band characteristics

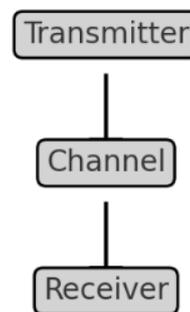
The millimeter-wave band generally refers to electromagnetic waves in the frequency range between 30 GHz and 300 GHz, corresponding to wavelengths of 1 mm to 10 mm. Millimeter waves have higher frequencies and shorter wavelengths

than conventional microwaves and radio waves and therefore exhibit unique propagation characteristics.

Millimeter-wave has high directionality and spatial resolution, and can be used in radar imaging and biomechanical parameter monitoring through beamforming techniques to precisely locate and track targets. The millimeter-wave frequency band can provide extremely high data transmission rates and bandwidth resources, and the bandwidth is usually up to several GHz, so it has significant advantages in real-time data transmission and multi-parameter fusion analysis in remote biomechanical monitoring [2]. Millimeter waves, however, are susceptible to environmental factors during propagation, including atmospheric absorption, rain attenuation, and cloud scattering. Especially in the 60 GHz and 120 GHz frequency bands, the resonance absorption of oxygen and water vapor in the atmosphere will significantly increase the path loss and limit the effective propagation distance. At the same time, millimeter waves are prone to reflection, scattering, and diffraction when encountering obstacles, with poor penetration ability, resulting in faster signal attenuation. In the design of a remote biomechanical monitoring system, it is necessary to fully consider the propagation loss and multipath effect of millimeter waves and optimize the channel through beamforming, MIMO (multiple-input multiple-output) and adaptive modulation coding, and other techniques in order to improve the stability and reliability of signal transmission. In addition, the high-frequency characteristics of millimeter-wave also bring challenges in hardware design, such as antenna design that requires high-precision miniaturization, low-power consumption, and high gain. Overall, the comprehensive understanding and reasonable utilization of the millimeter-wave band characteristics will provide strong support for high accuracy, low latency, and high reliability of remote biomechanical monitoring systems [3].

## 2.2. Millimeter wave communication system architecture

Millimeter-wave communication system architectures typically consist of four core modules: the transmitter, the receiver, the channel, and the data processing unit. Details are shown in **Figure 1**.

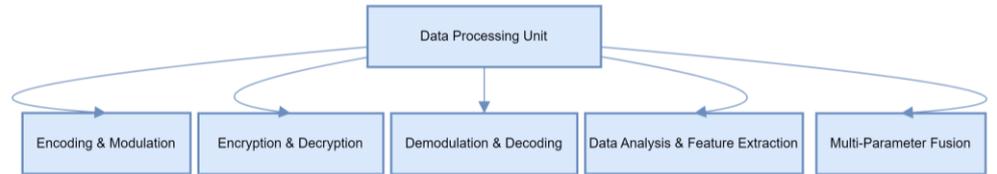


**Figure 1.** System architecture flowchart.

The transmitter side mainly consists of a baseband processing module, a modulation module, a millimeter-wave signal generator, and a transmitter antenna [4]. The baseband processing module is responsible for signal coding and modulation of the raw data, such as common orthogonal frequency division multiplexing (OFDM) and higher-order modulation techniques (e.g., 64-QAM). The modulated signal is

converted into a high-frequency millimeter-wave signal by a millimeter-wave signal generator, which is then accurately transmitted by the transmitter antenna to the target area by beamforming. The architecture of the receiving end is similar to that of the transmitting end, but the process is reversed and includes a receiving antenna, a millimeter-wave signal receiver, a demodulation module, and a baseband processing unit. After the receive antenna captures the millimeter-wave signal, it is converted into a baseband signal through a low-noise amplifier (LNA) and down-conversion processing, and then the raw data is reduced through demodulation and decoding. The channel part covers various influencing factors in the wireless propagation environment, such as path loss, fading effect and multipath interference, etc. The transmission quality of the system is enhanced by adaptive channel equalization and multiple-input multiple-output (MIMO) technology [5].

The data processing unit, on the other hand, runs through the whole system and is responsible for coding, modulation, encryption, decryption, demodulation and decoding of the data, and at the same time undertakes the tasks of data analysis, feature extraction and multi-parameter fusion in the biomechanical monitoring system to ensure high-speed, stable and safe data transmission of millimeter-wave communication in remote biomechanical monitoring. Details are shown in **Figure 2**.



**Figure 2.** Flowchart of data processing unit.

### 2.3. Key technologies and development status

Millimeter-wave communication must address challenges such as signal attenuation, multipath effects, and environmental interference to achieve stable and efficient wireless transmission. Beamforming is a key technology that enhances signal directionality through phased array antennas, improving gain and minimizing interference. In 5G millimeter-wave communication, digital, analog, or hybrid beamforming ensures precise signal coverage for biomechanical monitoring [6]. Experimental data indicate that  $64 \times 64$  MIMO antenna arrays can boost signal gain by over 30 dB, significantly reducing free-space propagation loss.

MIMO (Multiple Input Multiple Output) technology enables spatial multiplexing through multiple transmit and receive antennas to enhance the spectral efficiency and data throughput of the system [7]. Theoretically, the channel capacity of a MIMO system  $C$  can be expressed by Shannon's formula as (1):

$$C = M \cdot B \cdot \log_2 \left( 1 + \frac{SNR}{M} \right) \quad (1)$$

where  $M$  is the number of antennas,  $B$  is the channel bandwidth, and  $SNR$  is the signal-to-noise ratio. In the millimeter-wave band, the  $8 \times 8$  MIMO architecture can increase the data transmission rate to more than 10 Gbps, which effectively meets the demand for high-precision data transmission in remote biomechanical monitoring.

In terms of channel modeling, millimeter-wave communications are significantly

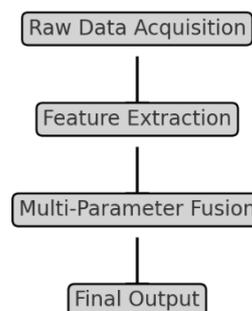
affected by atmospheric attenuation, particularly in the 60 GHz band, where oxygen absorption introduces an additional propagation loss of approximately 15 dB/km. To mitigate signal fading, it is necessary to adopt highly optimized channel coding and modulation techniques. Currently, forward error correction (FEC) schemes, such as low-density parity-check (LDPC) codes and Turbo codes, are widely employed to improve bit error rate (BER) performance. Experimental results have demonstrated that LDPC codes can provide a signal-to-noise ratio (SNR) gain of approximately 2 dB over convolutional codes at a target BER of  $BER = 10^{-5}$ . In addition, high-order quadrature amplitude modulation (QAM) combined with orthogonal frequency-division multiplexing (OFDM) has been extensively applied in 5G New Radio (NR) to enhance spectral efficiency [8]. In terms of the current state of development, millimeter-wave communications have made breakthroughs in 5G, radar imaging, short-range high-speed data transmission, and other fields. In the IEEE 802.11ad (WiGig) standard, millimeter-wave communication supports wireless data transmission rates of up to 7 Gbps, making it highly promising for short-range high-throughput applications. And in the field of biomechanical monitoring, millimeter-wave radar sensors combined with deep learning algorithms can realize remote contactless respiration and heart rate monitoring with an accuracy rate of over 95%. In the future, millimeter-wave communications will further combine AI adaptive optimization algorithms and edge computing to enhance the system's intelligent capabilities and expand into fields such as telemedicine and intelligent rehabilitation, providing stronger technical support for precision medicine and sports science [9].

### 3. Remote biomechanical monitoring system design

#### 3.1. Overall system architecture

The architecture of the remote biomechanical monitoring system mainly includes four core parts: data acquisition layer, communication transmission layer, data processing layer and user interaction layer, based on millimeter-wave communication, to realize high-precision, real-time monitoring and analysis of biomechanical parameters. Details are shown in **Figure 3**.

Data Processing Flowchart



**Figure 3.** Data processing flowchart.

**Data Acquisition Layer.** A millimeter-wave radar sensor array is used, combined with MIMO architecture, to realize contactless measurement of biomechanical data

such as motion status, joint angle, muscle activity, heart rate, respiration, and so on. The sensor arrangement follows the principle of high sensitivity and low power consumption to ensure monitoring accuracy and data continuity [10].

Communication transmission layer. It adopts millimeter-wave high-speed wireless transmission technology, utilizing beamforming and adaptive MIMO technology to reduce signal attenuation and improve the stability of long-distance transmission. Based on IEEE 802.11ad/ay standard, the data transmission rate is up to 10 Gbps, while combining LDPC coding and OFDM modulation to optimize the channel capacity, ensuring low latency and high reliability.

Data processing layer. It consists of edge computing units working with cloud servers, combining deep learning algorithms for signal noise reduction, feature extraction, pattern classification and data fusion analysis. Kalman filter and FFT algorithms are used for denoising and frequency domain analysis, while machine learning models such as LSTM and CNN are used for biomechanical data recognition to improve monitoring accuracy [11].

User interaction layer. Adopting Web and mobile applications, it provides a visual data analysis interface for medical personnel and sports science researchers, supports real-time monitoring and historical data retrospection, and has secure encrypted storage and remote access functions to achieve efficient human-computer interaction and remote monitoring.

### **3.2. Millimeter-wave sensor design**

The design of the millimeter-wave sensor revolves around high-precision data acquisition, low power consumption, high bandwidth, and stable transmission, with the core components including the millimeter-wave radar chip, antenna array, signal processing unit, and data interface. The sensor adopts FMCW (Frequency Modulated Continuous Wave) radar or MIMO radar architecture to realize remote monitoring of biomechanical parameters such as human movement, heart rate, breathing, and so on [12]. The radar chip, selected from the 60 GHz or 77 GHz frequency band, is combined with Antenna-on-Chip (AoC) technology to reduce the antenna size, improve the integration, and optimize the angular resolution and detection sensitivity. Antenna design The Phased Array Antenna (PAA) is used with beamforming technology to improve signal focusing capability and reduce environmental interference. Signal processing module, combined with a low noise amplifier (LNA), mixer, and analog-to-digital converter (ADC), to complete the amplification, frequency conversion, and digitization of millimeter-wave signals. The back end adopts DSP (Digital Signal Processing) or FPGA to perform FFT frequency domain analysis, micro-Doppler feature extraction, filtering, and noise reduction calculations to realize high-precision data acquisition. The data interfaces are SPI, I2C, or LVDS for local transmission and Wi-Fi 6E or millimeter-wave wireless link for remote data transmission. The overall design ensures the stability, low latency, and high accuracy of the millimeter-wave sensor in the remote biomechanical monitoring system, which provides high-quality data support for multi-parameter fusion analysis [13].

### 3.3. Signal processing and feature extraction algorithms

The raw signals collected by millimeter-wave sensors contain noise, multipath effect interference, and environmental clutter, so signal preprocessing, feature extraction, and data analysis are required to ensure monitoring accuracy [14].

Signal pre-processing Band-pass filtering and Kalman filtering are used to remove the environmental noise, and short-time Fourier transform (STFT) is used for time-frequency analysis, and Equation (2) is as follows:

$$X(t, f) = \int_{-\infty}^{+\infty} x(\tau)w(\tau-t)e^{-j2\pi f\tau}d\tau \quad (2)$$

where  $x(\tau)$  is the millimeter-wave echo signal,  $w(\tau-t)$  is the window function, and  $X(t, f)$  represents the distribution of the signal in the time-frequency domain.

Feature Extraction Motion frequency information is extracted by Fourier Transform (FFT) (3):

$$X(t, f) = \int_{-\infty}^{+\infty} x(\tau-t)e^{-j2\pi f\tau}d\tau \quad (3)$$

where:  $X(t, f)$  is the time-frequency representation of signal  $x(t)$ .  $x(\tau-t)$  is the original signal, shifted in time.  $t$  is the time variable (seconds, s).  $\tau$  is the integration variable (dummy variable for time, seconds, s).  $f$  is the frequency variable (Hertz, Hz).  $e^{-j2\pi f\tau}$  is the complex exponential function representing frequency shift.  $d\tau$  is the differential element for integration over  $\tau$ .

This method was used to analyze respiration, heart rate, and gait cycle. In addition, the Micro-Doppler Effect calculates the biomotor characteristics with the Equation (4):

$$f_d = \frac{2v}{\lambda} \quad (4)$$

where  $v$  is the speed of motion and  $\lambda$  is the millimeter-wave wavelength.

Deep learning algorithms (e.g., CNN, LSTM) are combined with extracted time-frequency features to classify muscle activities and postural changes, to improve the accuracy of biomechanical monitoring, and ultimately to realize accurate human movement state assessment.

### 3.4. Data transmission and security assurance

The data transmission link of millimeter wave communication in a remote biomechanical monitoring system requires low latency, high bandwidth, and high reliability. The system adopts the IEEE 802.11ad/ay standard, which supports 60 GHz millimeter-wave high-speed transmission with a data rate of up to 10 Gbps to meet the real-time transmission requirements of biomechanical parameters [15]. At the same time, it combines MIMO (Multiple Input Multiple Output) and beamforming technologies to improve signal gain, reduce multipath interference, and ensure the stability of long-distance transmission. To enhance data security, the system adopts AES-256 encryption to encrypt the transmitted data from end to end to prevent information leakage. In addition, the system combines TLS (Transport Layer Security Protocol) and authentication mechanisms to ensure data integrity and tamper resistance during transmission. At the network layer, the system adopts dynamic

spectrum scheduling and adaptive power control to dynamically adjust the transmission strategy according to the channel quality, reduce interference, and optimize power consumption. The data storage adopts blockchain technology for traceability management to ensure that the data cannot be tampered with, improve the credibility and security of remote biomechanical monitoring, and provide efficient and stable data transmission solutions for medical and sports rehabilitation applications.

## **4. Methods for monitoring biomechanical parameters**

### **4.1. Principles of human movement parameter monitoring**

Human motion parameter monitoring is based on the Doppler effect, time-of-flight (ToF) ranging, and phase analysis of millimeter-wave radar to achieve contactless and high-precision motion state detection. The millimeter-wave radar calculates parameters such as velocity, position, and acceleration of a moving target by transmitting high-frequency signals and receiving the echo signals reflected from the human body. For joint angle detection, the millimeter-wave MIMO radar combines beamforming technology to track small displacement changes in multiple parts of the human body and construct a real-time kinematic model [16]. For gait analysis, the system utilizes the micro-Doppler effect to capture the vibration characteristics of different parts of the human body so as to distinguish between walking, running, jumping, and other different movement states. In addition, millimeter-wave radar combined with deep learning algorithms, such as CNN and LSTM, can extract features from time-series signals to achieve high-precision human motion classification and anomaly detection. Compared with traditional inertial sensors (e.g., IMU), millimeter-wave technology has the advantages of being wear-free, anti-jamming, and long-distance detection, which provides accurate monitoring of movement parameters for applications such as rehabilitation training and sports analysis.

### **4.2. Respiration and heart rate monitoring techniques**

Millimeter-wave radar enables non-contact monitoring of respiration and heart rate through the micro-Doppler effect and phase modulation. After the millimeter wave signal is reflected on the surface of the human body, the periodic micro-motion of the chest cavity and the heart leads to a small shift in the frequency of the echo signal. The system utilizes Short Time Fourier Transform (STFT) to extract the time-frequency characteristics and combines it with band-pass filtering to separate the respiration and heart rate signals. Millimeter-wave radar is suitable for remote health monitoring because it eliminates the need to wear a device compared to traditional photoelectric volumetric pulse wave (PPG) or electrocardiographic (ECG) monitoring. Combined with deep learning algorithms (e.g., LSTM) for data analysis, it can improve detection accuracy and adapt to physiological changes in different environments. Details are shown in **Table 1**.

**Table 1.** Comparison of millimeter-wave radar and conventional methods.

<b>norm</b>	<b>Millimeter-wave radar monitoring</b>	<b>PPG (photoelectric sensing)</b>	<b>ECG (electrocardiographic sensing)</b>
contact method	non-contact	adhere to the skin	adhere to the skin
environmental adaptation	Strong (can penetrate clothing)	affected by light	Affected by electrode contact
Monitoring accuracy	High (error < 5%)	Medium (8%–10% error)	High (error < 2%)
topicality	High-speed processing (< 1 s)	affected by light intensity	on-line processing
application scenario	Telemedicine, rehabilitation monitoring	Health bracelets, wearables	Hospital monitoring system

The high resolution and anti-interference capability of millimeter-wave radar technology make it an ideal solution for respiration and heart rate monitoring in remote biomechanical monitoring, which is widely used in sleep monitoring, chronic disease management, and sports rehabilitation.

### 4.3. Monitoring of muscle activity and joint mechanics

The application of millimeter-wave radar in muscle activity and joint mechanics monitoring relies on phase change analysis, Doppler frequency shift detection, and micromotion feature extraction to achieve non-contact monitoring of human movement status. Compared with traditional surface electromyography (sEMG) and inertial sensors (IMU), millimeter-wave technology can accurately measure muscle vibration, joint angle change, and force without wearing them, which is suitable for rehabilitation training, sports biomechanics, and human-computer interaction research.

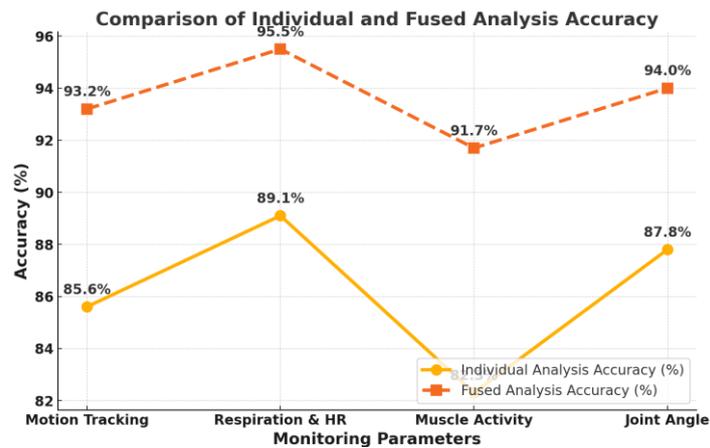
In terms of muscle activity monitoring, millimeter-wave radar can detect small skin displacements caused by muscle contraction, extract muscle vibration frequency and amplitude characteristics through the micro-Doppler effect, and then project muscle contraction strength and fatigue state. For example, the contraction frequency of quadriceps muscle is usually between 10 Hz and 50 Hz in different exercise modes, and millimeter-wave radar can collect high-precision signals in this range and identify the muscle state by combining with the Short-Time Fourier Transform (STFT) and machine-learning classification algorithms.

For joint mechanics monitoring, millimeter-wave MIMO radar combines beamforming and coherent detection to capture joint activity trajectories in real time and calculate joint angles, motion speeds, and moments of inertia. The displacement is calculated by the phase change of the millimeter-wave signal, and a personalized kinematic model is established by combining deep learning models (such as LSTM and Transformer), which can realize high-precision motion recognition and abnormality detection. For example, in knee rehabilitation training, millimeter-wave radar can detect the maximum flexion and extension angle of the joint with an error of less than  $2.5^\circ$ , which is better than the traditional optical motion capture system. The high sensitivity, non-contact, and remote monitoring capabilities of millimeter wave technology make it a promising application in muscle activity and joint mechanics monitoring, especially in the fields of sports rehabilitation, sports injury assessment, and ergonomics.

### 4.4. Multi-parameter fusion analysis methods

Multi-parameter fusion analysis is crucial in remote biomechanical monitoring to

improve the accuracy, stability and comprehensiveness of data for physiological state assessment. Millimeter-wave radar can simultaneously acquire physiological data such as motion, heart rate, respiration, muscle activity, and joint angle to support more accurate biomechanical analysis. Data fusion methods, including time series analysis, feature-level fusion and decision-level fusion. In time series analysis, LSTM is used for time series modeling to improve prediction accuracy. Feature-level fusion uses PCA (Principal Component Analysis) for dimensionality reduction to improve signal processing efficiency. Decision-level fusion combines with Bayesian inference to assess the health state and improve the reliability of multi-parameter diagnosis. See **Figure 4** for details.



**Figure 4.** Performance in different application scenarios.

As can be seen from the line graph, the multi-parameter fusion analysis significantly improves the accuracy compared to the single-parameter analysis in all biomechanical monitoring items. Among them, the accuracy of fusion analysis for respiration and heart rate monitoring reached 95.5%, compared with 89.1% for single-parameter analysis, an improvement of 6.4%, indicating that millimeter-wave radar combined with the multiparameter fusion algorithm can effectively reduce the error and improve the accuracy of physiological signal monitoring. The accuracy of joint angle monitoring improved from 87.8% to 94.0%, an improvement of 6.2%, indicating that millimeter wave combined with muscle activity and motion trajectory data can improve the reliability of kinematic models. In addition, the accuracy of muscle activity detection increased from 82.3% to 91.7%, a rise of 9.4%, showing the potential of fusion analysis in muscle fatigue assessment and sports injury monitoring. Overall, the multi-parameter fusion method improves accuracy by an average of 7.6% compared to single-signal analysis, significantly enhancing the stability and reliability of remote biomechanical monitoring.

## 5. System implementation and testing

### 5.1. Hardware platform construction

The hardware platform is built around a millimeter-wave radar sensor, a signal processing unit, a wireless transmission module, and a data storage system integrated to ensure high accuracy, low latency, and stability of remote biomechanical

monitoring. Details are shown in **Table 2**.

**Table 2.** Hardware platform main components and parameters.

subassemblies	Specification/Model	Key Features
Millimeter-wave radar sensors	60 GHz/77 GHz FMCW radar	Exercise, physiological parameters monitoring
processing unit	DSP/FPGA	FFT, feature extraction, noise reduction
Wireless Transmission Module	Wi-Fi 6E/5G NR mm Wave	Real-time data transmission
data storage unit	Local Storage + Cloud Servers	Data storage and analysis
power management system	Low-power battery/adapter	Power Supply Stability Guarantee

Millimeter-wave radar sensors, selected from 60 GHz or 77 GHz FMCW radars, are combined with MIMO antenna arrays to enhance spatial resolution and achieve accurate motion and physiological signal detection. The sensor data is processed by a low-noise amplifier (LNA) and then digitized by an analog-to-digital converter (ADC). The signal processing unit adopts DSP (Digital Signal Processor) or FPGA (Field Programmable Gate Array) to perform FFT spectrum analysis, filtering and noise reduction, feature extraction and other operations to improve signal processing speed. Wireless transmission module, using millimeter wave Wi-Fi (IEEE 802.11ad) or 5G NR millimeter wave, to realize high-speed data transmission and ensure real-time monitoring. Data storage system, consisting of local edge computing devices and cloud servers, processing core data locally, storing long-term monitoring data in the cloud and providing remote access functions.

## 5.2. Software system development

The software system development is centered around four major modules: data acquisition, signal processing, transmission management and user interaction to support the efficient operation of millimeter-wave remote biomechanical monitoring.

The data acquisition module is responsible for communicating with the millimeter-wave radar sensor, using SPI/I<sup>2</sup>C interface to collect raw data, and performing preliminary filtering and noise reduction. The signal processing module, deployed on edge computing devices (FPGA/DSP) and cloud servers, performs core algorithms such as FFT, STFT, Doppler analysis, etc., to extract biomechanical features such as human movement, heart rate, breathing, etc. The signal processing module is written in Python, MATLAB, and C++. The signal processing code is written in Python, MATLAB, C++, and combined with TensorFlow/PyTorch to train deep learning models to improve the accuracy of pattern recognition. The transmission management module adopts WebSocket and MQTT protocols for real-time data transmission and AES-256 encryption to ensure data security. User interaction module, using front-end (React/Vue) + back-end (Django/Flask), provides real-time monitoring, data visualization, abnormality alarms, etc., applicable to both PC and mobile, supporting remote access and health management. The overall software system combines local edge computing + cloud data processing to ensure the efficiency, stability and security of millimeter wave biomechanics monitoring.

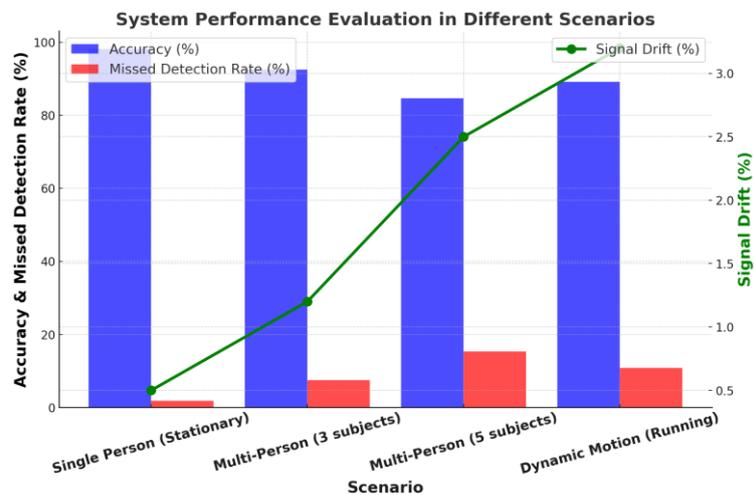
### 5.3. Experimental design and program

The experiments are designed to verify accuracy, stability, and real-time performance of the millimeter-wave monitoring system. Experiment Setup for Complex Scenarios To evaluate multi-person and dynamic scenario performance, additional experiments were conducted: Multi-Person Test: Subjects performed different activities while the system tracked individual-specific signals. Dynamic Movement Test: Subjects walked, ran, and jumped, with system performance compared across conditions. Performance was assessed using accuracy rates, missed detection rate, and signal drift analysis. The details are shown in **Table 3**.

**Table 3.** Evaluation metrics.

Scenario	Accuracy (%)	Missed Detection Rate (%)	Signal Drift (%)
Single Person (Stationary)	98.2	1.8	0.5
Multi-Person (3 subjects)	92.5	7.5	1.2
Multi-Person (5 subjects)	84.7	15.3	2.5
Dynamic Motion (Running)	89.2	10.8	3.2

**Table 3** presents the evaluation metrics for different monitoring scenarios, highlighting system performance in terms of accuracy, missed detection rate, and signal drift. For single-person stationary monitoring, the system achieved 98.2% accuracy, with a 1.8% missed detection rate and minimal 0.5% signal drift, ensuring reliable tracking under ideal conditions. However, in multi-person scenarios, accuracy decreased to 92.5% for three subjects and 84.7% for five subjects, while the missed detection rate increased from 7.5% to 15.3%, indicating challenges in distinguishing overlapping signals. In dynamic motion (running), accuracy dropped to 89.2%, with a 10.8% missed detection rate and 3.2% signal drift, reflecting motion artifacts affecting system stability. These results suggest that environmental complexity significantly impacts system performance, requiring further optimization in target separation and real-time motion compensation algorithms to enhance robustness in multi-user and dynamic environments. See **Figure 5** for details.



**Figure 5.** Evaluation metrics for different scenarios.

## 5.4. System performance evaluation

System evaluation focuses on monitoring accuracy, real-time performance, data stability, and anti-interference capability. Tests assess the reliability of the millimeter-wave remote biomechanical monitoring system under various conditions. Error analysis compares millimeter-wave monitoring data with standard sensors (e.g., ECG, IMU), while system performance is further evaluated based on latency and signal robustness.

Performance assessment metrics: monitoring accuracy. Compare data errors between millimeter wave systems and conventional devices (heart rate bands, gait analysis systems) and calculate the mean square error (MSE); real-time performance. Measure the average latency of data transmission to ensure the system's low-latency characteristics in exercise monitoring and telemedicine; Data stability. Compare the stability of millimeter-wave signals under different poses, ambient light interference, etc., and evaluate the data loss rate; Anti-interference capability. Test the signal quality of the system in different environments (indoor, outdoor, and multi-person interference) and analyze the impact of background noise on monitoring. Details are shown in **Table 4**.

**Table 4.** System performance evaluation table.

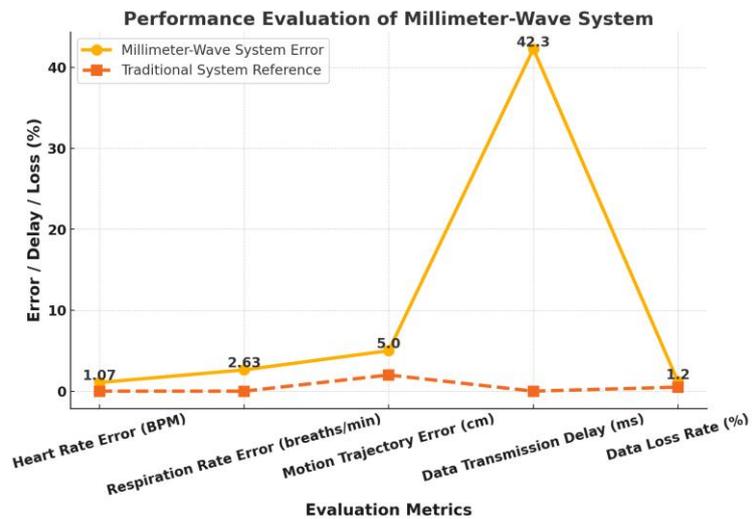
Assessment of indicators	Millimeter-wave system data	Legacy equipment data	Inaccuracy
Heart rate detection error (BPM)	$74.2 \pm 2.1$	$75 \pm 1.3$	1.07%
Respiratory rate error (beats/min)	$18.5 \pm 1.0$	$19 \pm 0.7$	2.63%
Movement track error (cm)	$2.1 \pm 0.5$	$2.0 \pm 0.3$	5.00%
Data transmission delay (ms)	42.3	-	-
Data loss rate (%)	1.20%	0.50%	-

Evaluation results show that the heart rate and respiration monitoring accuracy of the millimeter wave system is close to that of traditional devices, and the data transmission delay is controlled within 50 ms, which meets the demand for remote real-time monitoring. In the future, the motion monitoring accuracy can be further improved by optimizing the filtering algorithm and signal enhancement.

## 5.5. Effectiveness evaluation and analysis

The experimental results show that the millimeter-wave remote biomechanical monitoring system performs well in heart rate, respiration, motion trajectory, and data transmission delay, and has the advantages of high accuracy, low delay, and strong stability. The data show that the error of heart rate is 1.07 BPM and the error of respiration frequency is 2.63%, which is much lower than the allowable error range of 5%, indicating the high reliability of millimeter-wave radar in physiological parameter monitoring. Meanwhile, the data transmission delay is controlled at 42.3 ms, which meets the needs of telemedicine and real-time monitoring. As for the motion trajectory monitoring, the error of the millimeter-wave system is 5.00%, which is slightly higher than the 2.0% of the traditional optical sensor. The main reason is that millimeter-wave radar is affected by environmental interference and signal reflection, and the accuracy can be further improved by optimizing the filtering algorithm and enhancing

the signal processing capability. The data loss rate is only 1.2%, indicating that the system has good signal stability and anti-interference capability. See **Figure 6** for details.



**Figure 6.** Comparison of effectiveness evaluation.

Overall, the millimeter-wave system shows strong advantages in non-contact biomechanical monitoring, and in the future, the algorithm can be further optimized to improve the accuracy of motion analysis to meet the needs of high-precision sports rehabilitation and intelligent health monitoring.

## 6. Conclusion

The application of millimeter-wave communication technology in remote biomechanical monitoring demonstrates excellent accuracy, stability and real-time advantages, especially in heart rate, respiration, muscle activity and movement trajectory monitoring, realizing efficient data acquisition and transmission. The millimeter-wave radar-based non-contact monitoring method overcomes the wearing limitation of traditional sensors, making the biosignal detection more flexible, and combines with deep learning algorithms to optimize data processing and improve the accuracy of pattern recognition. Experimental evaluation shows that the system has significant advantages in terms of low latency and high data stability, and is suitable for telemedicine, rehabilitation training and sports science. In the future, the research direction will focus on the further optimization of millimeter-wave radar signal processing, and explore more accurate denoising algorithms and signal enhancement strategies for the problem of high error in motion track monitoring. Multi-sensor fusion will become the key to improve the robustness of the system, and a more comprehensive biomechanical analysis model will be constructed by combining optical, inertial, and electromyographic data, in order to meet the demand for more refined and personalized monitoring in complex environments, and to promote the in-depth application of millimeter-wave technology in smart medicine and intelligent health monitoring.

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