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Molecular & Cellular Biomechanics 2025, 22(1), 714.
https://doi.org/10.62617/mcb714

Article

Research on synchronous acquisition and processing algorithm of biomechanical data in mobile network environment

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CITATION

Zhang X. Research on synchronous acquisition and processing algorithm of biomechanical data in mobile network environment. Molecular & Cellular Biomechanics. 2025; 22(1): 714.
https://doi.org/10.62617/mcb714

ARTICLE INFO

Received: 5 November 2024
Accepted: 14 November 2024
Available online: 8 January 2025

Abstract: In this study, the problem of synchronous acquisition and processing of biomechanical data in a mobile network environment is thoroughly investigated. An efficient and stable synchronous acquisition and processing algorithm is proposed, and its advantages in real-time and accuracy are experimentally verified. The results show that the algorithm significantly outperforms the traditional algorithm in the process of synchronous data acquisition and processing, and provides technical support for the wide application of biomechanical data in the fields of telemedicine and sports monitoring. The current status of the algorithm in addressing the challenges in mobile network environments is reported, and future optimisation directions are proposed to adapt to more complex network environments.

Keywords: mobile networks; biomechanics; simultaneous data acquisition; processing algorithms

1. Introduction

As an important parameter for understanding and evaluating human motor performance, physiological state and pathological changes, biomechanical data have been increasingly used in the fields of exercise physiology, rehabilitation medicine, sports training and smart health monitoring [1]. With the rapid development of the Internet of Things (IoT), wireless sensor networks (WSN), mobile communications and other technologies, biomechanical data acquisition and processing are gradually migrating from the traditional laboratory environment to the more flexible and convenient mobile network environment [2]. This shift has greatly expanded the application scenarios of biomechanical data, making remote medical monitoring and real-time motion analysis possible. However, data transmission in mobile network environments faces many challenges, such as uneven signal coverage, network bandwidth limitations, data transmission delays, packet loss phenomena, and connection interruptions due to network switching [3]. These problems put forward higher requirements for real-time synchronous acquisition and processing of biomechanical data. Especially in application scenarios that require high precision and low latency, how to ensure the integrity and accuracy of data has become an urgent problem [4]. Aiming at the above challenges, this paper thoroughly researches the key technologies for synchronous acquisition and processing of biomechanical data in mobile network environment.

2. Related work

2.1. Biomechanical data acquisition techniques

Biomechanical data acquisition technology is a key link in the study of biomechanical parameters, which covers many aspects such as sensor technology, signal processing technology and data transmission technology [5]. With the progress of microelectronics technology and material science, domestic and foreign researchers have developed a variety of high-performance biomechanical sensors for diverse application scenarios.

2.1.1. Sensor technology

Sensor technology plays a crucial role in the field of biomechanical data acquisition. Current research focuses on four types: miniaturised acceleration sensors, multifunctional pressure sensors, flexible sensors and optical sensors [6]. Miniaturised acceleration sensors make use of microelectromechanical systems (MEMS) technology to achieve small size, low power consumption and high accuracy, which can accurately capture the human body's movement state and dynamic changes. Multi-functional pressure sensors, on the other hand, can simultaneously measure multi-dimensional forces such as pressure and shear, and are widely used in gait analysis, seat pressure distribution measurement and other fields. Flexible sensors, with their good flexibility and adaptability, accurately capture biomechanical data without interfering with the body's natural movement, and are suitable for scenarios such as sports monitoring and rehabilitation assistance [7]. Optical sensors, on the other hand, provide important support for biomechanical research by non-invasively measuring parameters such as heart rate, oxygen saturation, and three-dimensional motion trajectory through photoelectric volumetric tracing (PPG) and motion capture technology.

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2.1.3. Data transmission technology

The research of data transmission technology is committed to solving the problem of data synchronisation and real-time transmission in mobile network environment. To this end, researchers have carried out the following related work: firstly, wireless transmission protocols such as ZigBee, Wi-Fi, Bluetooth, etc. are optimized for the characteristics of wireless sensor networks to improve the efficiency and reliability of data transmission; secondly, network coding and redundant transmission strategies are proposed to effectively overcome the packet loss in mobile networks by sending coded versions of data on multiple transmission paths problem and improve the data arrival rate; finally, combining edge computing and cloud computing, some data processing tasks are migrated from the cloud to the edge of the network, which realises the pre-processing of the data source, thus reducing the amount of data to be transmitted and lowering the transmission delay [9].

2.2. Data transmission technology in the mobile network environment

Data transmission technology in a mobile network environment is central to supporting real-time simultaneous acquisition and processing of biomechanical data. With the iterative updating of wireless communication technologies, from 3G to 4G and the current rapidly developing 5G technology, the rate, capacity and latency of data transmission have been significantly improved [10].

2.2.1. Development of wireless communication technologies

The third generation of mobile communication technology (3G) made video calls and mobile Internet access possible by increasing data transmission rates compared to its predecessor, but still showed limitations in handling large-scale data transmission. Subsequently, the fourth-generation mobile communication technology (4G) further improved the data transmission speed and reduced the latency to provide better support for real-time transmission of biomechanical data, and its wide coverage and high transmission efficiency facilitated the wide application in areas such as mobile health monitoring [11]. The current fifth-generation mobile communication technology (5G), as the frontier of wireless communication technology, not only achieves a leap in data transmission rate, which can theoretically reach tens of Gbps, but also achieves significant improvement in connection density and delay, etc., and its low-latency characteristics are crucial for biomechanical data transmission with high real-time requirements.

2.2.2. Data transmission optimisation algorithm

Researchers have proposed various optimisation algorithms for the data transmission problem in the mobile network environment. Firstly, in order to reduce the packet loss problem caused by signal fading and interference, packet loss recovery algorithms such as Automatic Retransmission Request (ARQ) and Forward Error Correction (FEC) were developed to guarantee data integrity [12]. Secondly, channel coding techniques such as convolutional coding, Turbo coding and low density parity check (LDPC) are used to improve the reliability of data transmission in wireless channels. At the network layer, researchers have proposed optimisation strategies such as mobile IP technology, network coding, and multipath transmission to adapt to the dynamic changes in the mobile network and improve transmission efficiency. In addition, adaptive modulation and coding (AMC) techniques are able to adjust the modulation method and coding rate according to the real-time state of the wireless channel to maximise the transmission rate and reliability [13]. Finally, edge computing-assisted data processing achieves data preprocessing and caching by deploying computing resources at the edge of the mobile network to reduce the amount of transmitted data, lower the latency, and improve the system response speed [14].

3. Algorithm design

3.1. Data synchronisation acquisition algorithm

3.1.1. Sensor node layout

In order to further deepen the study of sensor node layout, we can consider the following aspects of optimisation and formula derivation:

Optimisation strategy 1: Optimal sensor node layout based on spatial coverage and signal overlap

In sensor node layout, in addition to uniform distribution and density clustering, optimisation strategies can be used to ensure the maximisation of spatial coverage and minimisation of signal overlap. The following is the mathematical model of the optimal layout problem:

Let C be the set of all possible locations in the monitoring area, S be the set of selected sensor node locations, and R be the coverage radius of the sensor nodes. The objective is to minimise the uncovered area while reducing the signal overlap between nodes. The problem can be expressed as:

$$\min \text{Size of uncovered areas} + \lambda \cdot \text{Signal overlap area}$$

$$\text{s.t.} \forall c \in C, \exists s \in S \text{ such that } d(s,c) \leq R$$

$$|S| = N$$

where λ is a weighting factor that weighs the uncovered area and the signal overlap, and $d(s,c)$ is the Euclidean distance between locations s and c.

Optimisation strategy II: Sensor node layout based on multi-hop communication

In a large monitoring area, the coverage of a single sensor node is limited, so multi-hop communication needs to be considered [15]. The following is the optimisation formula for node layout based on multi-hop communication:

Let $G(V,E)$ be the communication graph of sensor nodes, where V is the set of nodes and E is the set of edges. The objective is to maximise the connectivity of the network. The problem can be expressed as:

$$max \quad \text{Connectivity} = \sum_{v \in V} \quad \deg(v)$$

$$\text{s.t.} \forall v \in V, d(u,v) \leq R, \text{ for some } u \in V \text{ with } u \neq v$$

where deg (v) is the degree of node v and denotes the number of nodes directly connected to node v.

Optimisation Strategy III: Sensor Node Layout Based on Energy Efficiency

In wireless sensor networks, energy efficiency is a key consideration. Following is the optimisation formula for node layout based on energy efficiency:

Let E_{total} be the total energy consumption of the network, E_{comm} be the communication energy consumption and E_{sense} be the sensing energy consumption.

The objective is to maximise the life cycle of the network. The problem can be expressed as:

$$max \quad \text{Network Life Cycle} = \frac{E_{total}}{E_{comm} + E_{sense}}$$

$$\text{s.t.} \forall s \in S, E_{comm}(s) + E_{sense}(s) \leq E_{max}$$

where E_{max} is the maximum energy capacity of a single sensor node.

3.1.2. Time synchronisation

To expand on time synchronisation, we can consider more advanced time synchronisation algorithms [16]. Such as Network Time Protocol version 4 (NTPv4) and Precision Time Protocol (PTP) and their application and optimisation in mobile network environments.

(1) Time Synchronisation Optimisation for NTPv4

NTPv4 is an updated version of NTP that provides better time synchronisation accuracy and security. In NTPv4, the algorithms for time synchronisation can be further optimised to reduce network latency and clock deviation. Following are the formulas for time synchronisation optimisation based on NTPv4:

Let T_1, T_2, T_3, T_4 be the timestamps of client sending request, server receiving request, server sending response and client receiving response respectively. Considering the symmetry of the network path, we can calculate the round trip delay 'RTT' and the offset θ as follows:

$$\text{RTT} = T_4 - T_1 - (T_3 - T_2)$$

$$\theta = \frac{(T_2 - T_1) + (T_3 - T_4)}{2}$$

In order to improve the synchronisation accuracy, NTPv4 uses a filtering algorithm to smooth out the time deviation as shown below:

$$\theta_{\text{new}} = \alpha \cdot \theta_{\text{old}} + (1 - \alpha) \cdot \theta_{\text{new,raw}}$$

where α is the filter coefficient, θ_{old} is the last computed time deviation, and $\theta_{\text{new,raw}}$ is the newly computed time deviation.

(2) Synchronisation algorithm of Precision Time Protocol (PTP)

Precision Time Protocol (PTP) is a protocol used to synchronise computer clocks in a network, which provides sub-microsecond time synchronisation accuracy. The synchronisation algorithm of PTP can be expressed as:

Let $T_{m1}, T_{m2}, T_{s1}, T_{s2}$ be the timestamps for the master clock to send synchronisation messages, the slave clock to receive synchronisation messages, the slave clock to send follow messages and the master clock to receive follow messages, respectively. The synchronisation algorithm for PTP is as follows:

$$\text{Offset} = \frac{(T_{m2} - T_{m1}) - (T_{s2} - T_{s1})}{2}$$

$$\text{Delay} = (T_{m2} - T_{m1}) - (T_{s2} - T_{s1})$$

where Offset is the time deviation between the master and slave clocks and Delay is the round trip delay of the synchronisation message. To further improve the synchronisation accuracy, the PTP protocol can use the following formula to correct the clock:

$$\text{Corrected Time} = \text{Current Time} - \text{Offset} - \frac{\text{Delay}}{2}$$

(3) Time Synchronisation Challenges in a Mobile Network Environment

In mobile network environments, time synchronisation faces challenges such as uneven signal coverage and frequent network switching [17]. To cope with these challenges, the following strategies can be adopted: use multipath time synchronisation, which reduces the instability of a single path by synchronising clocks over multiple network paths. Implementing time synchronisation algorithms specific to mobile networks, such as mobile base station based time synchronisation, taking into account the mobility and signal coverage of the base station.

3.1.3. Data preprocessing

Data preprocessing is an important step in biomechanical data analysis, which includes filtering, denoising, normalisation, and missing value processing [18].

(1) Low-pass filter: A low-pass filter is used to remove high-frequency noise and retain low-frequency useful signals. The above mentioned formula for Butterworth low pass filter can be further extended to n order Butterworth filter:

$$\mathrm{H}(\omega) = \frac{1}{\sqrt{1 + (\frac{\omega}{\omega_c})^{2n}}}$$

where ω_c is the cutoff frequency, n is the order of the filter, and ω is the corner frequency. A higher order results in a steeper roll-off of the filter at the cutoff frequency.

(2) Wavelet transform: The wavelet transform is a time-frequency analysis tool that is well suited for denoising non-stationary biomechanical signals. The process of multiscale denoising can be achieved by the following steps:

Perform multi-scale wavelet decomposition of the signal:

$$W_f(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t) \psi\left(\frac{t-b}{a}\right) dt$$

Threshold the wavelet coefficients to remove noise:

$$\hat{W}_f(a,b) = \begin{cases} W_f(a,b) - \lambda \text{if} \left| W_f(a,b) \right| > \lambda \\ 0 \text{ otherwise} \end{cases}$$

where λ is the threshold, which is usually determined based on the noise level. The signal is reconstructed using the processed wavelet coefficients:

$$\mathrm{f}(t) = \sum_a \sum_b \hat{W}_f(a,b) \psi(\frac{t-b}{a})$$

(3) Median Filter: The median filter is another nonlinear filter commonly used to remove impulse noise with the following equation:

$$\mathrm{y}[n] = \mathrm{median}(x[n-k], x[n-k+1], \ldots, x[n+k-1], x[n+k])$$

where $y[n]$ is the filtered signal, $x[n]$ is the original signal, and k is the filter window size.

(3) Normalisation: Normalisation allows the data to be on the same scale for easy comparison and analysis. One of the most commonly usednormalisation methods is max-min normalisation:

$$x_{\text{norm}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

where x_{norm} is the normalised value, x is the original data, and $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the data respectively.

(5) Missing value processing: for the processing of missing values, interpolation methods can be used, such as linear interpolation:

$$x_{\text{miss}} = \frac{x_i + x_{i+1}}{2}$$

where x_{miss} is the result of positional interpolation of missing values, and x_i and x_{i+1} are the data points before and after the missing values.

3.2. Data processing algorithms

3.2.1. Data fusion

Data fusion techniques improve the accuracy and reliability of data by integrating information from multiple sensor sources. Below are a few common data fusion techniques and their formulas:

Weighted average fusion: data fusion by weighted average of data from different sensors with the following formula:

$$\left[\hat{X} = \sum_{i=1}^{N} w_i X_i\right]$$

where $\hat{X}$ is the fused data, X_i is the data of the i sensor, w_i is the corresponding weight, and $\sum_{i=1}^{N} w_i = 1$. the weights are chosen based on the confidence level of the sensor data, and their impact on the system performance is verified experimentally.

Kalman filter: a recursive optimal estimator for state estimation of linear Gaussian systems with the following update equation:

$$\hat{X}k|k = \hat{X}k|k-1 + K_k(Z_k - H_k\hat{X}k|k-1)$$

where $\hat{X}k|k$ is the state estimate at moment k, Z_k is the observation at moment k, H_k is the observation matrix, and K_k is the Kalman gain. the Kalman gain is determined through a priori knowledge of the system model and noise characteristics, and its accuracy directly affects the performance of the state estimation.

3.2.2. Feature extraction

Feature extraction is the extraction of information useful for classification and recognition from the original data. The following are some commonly used feature extraction methods and their formulas:

Fourier Transform: used to extract the frequency domain features of the signal, the formula is as follows:

$$\mathrm{F}(\omega) = \int_{-\infty}^{+\infty} f(t)e^{-j\omega t}dt$$

where $F(\omega)$ is the Fourier transform of the signal $f(t)$, ω is the angular frequency, and j is an imaginary unit. the choice of parameters in the transformation is based on signal characteristics and has a significant impact on the accuracy of the feature representation.

Principal Component Analysis (PCA): used for dimensionality reduction, which aims to find new eigenvectors that maximise the variance of the data with the following formula:

$$\mathrm{C} = \frac{1}{n-1}\sum_{i=1}^{n} (\mathrm{x}_i - \mu)(\mathrm{x}_i - \mu)^T$$

where C is the covariance matrix, x_i is the i sample, and μ is the sample mean. the selection of the number of principal components in PCA is based on the cumulative contribution ratio of variance, which has a significant impact on the data dimensionality reduction effect and subsequent classification performance.

3.2.3. Pattern recognition

Pattern recognition is the process of classifying and recognising data using machine learning algorithms [19]. Following are some of the commonly used machine learning algorithms and their formulas:

Support Vector Machine (SVM): used for classification problems where the goal is to find a hyperplane that maximises the spacing between datasets with the following formula:

$$\min_{\mathrm{w},b} \frac{1}{2}|\mathrm{w}|^2$$

$$\text{subject to} y_i(\mathrm{w}^T\mathrm{x}_i + b) \geq 1, i = 1, \dots, n$$

where w is the normal vector of the hyperplane, b is the bias term, and y_i is the category label. the kernel function and penalty parameters in SVMs are chosen through cross-validation, and they have a significant impact on the generalization ability of the classifier.

Neural Networks: feature learning and classification by means of multilayer perceptrons, the output of which can be expressed as:

$$\mathrm{z} = \sigma(\mathrm{Wx} + \mathrm{b})$$

where z is the output, W is the weight matrix, b is the bias vector, and σ is the activation function. the structural parameters (e.g., number of layers, number of neurons per layer) and training parameters (e.g., learning rate, batch size) in the neural network are tuned experimentally, and they have a significant impact on the training speed and classification accuracy of the model.

4. Experiment and analysis

4.1. Experimental environment

In order to comprehensively verify the performance and efficiency of the proposed algorithm in practical applications, we constructed an advanced mobile network-based experimental platform for biomechanical data acquisition and processing [20]. The design of this platform fully considers various factors such as sensor accuracy, network transmission stability, and data processing capability. The following is a detailed expansion and in-depth description of the experimental environment:

(1) Sensor nodes:

Sensor type and specifications: We chose the MPU6050 six-axis motion tracking sensor, which integrates a 16-bit accelerometer and gyroscope to provide highly accurate motion data. In addition, we extended other types of sensors such as pressure sensors (e.g., Bosch BME280) and EMG sensors (e.g., MyoWare Muscle Sensor) to capture more comprehensive biomechanical data.

Sensor Layout: Sensor nodes are laid out according to a human kinematic model to ensure coverage of key movement joints and muscle groups. Each sensor node is equipped with a microcontroller (e.g., Arduino or Raspberry Pi) for local data preprocessing and initial time synchronization.

(2) Mobile network devices:

Network device specifications: we used a Huawei 5G CPE Pro router that supports the 5G NSA/SA network standard to provide high-speed, low-latency wireless network connectivity. In addition, the device supports the Wi-Fi 6 standard to ensure the rate and stability of wireless communication with the sensor nodes.

Mobile Terminal: The mobile terminal used in the experiment is the latest smartphone or tablet PC with high-resolution display and powerful processing capability, which is used for real-time monitoring of data acquisition status and preliminary data analysis.

(3) Server:

Server Configuration: The server is a Dell PowerEdge R740, equipped with high-performance CPU (e.g., Intel Xeon Gold Series), large-capacity memory, and high-speed SSD storage to meet the needs of big data processing and analysis.

Data processing software: Professional data processing and analysis software, such as MATLAB, Python (with libraries such as NumPy, SciPy, Pandas, etc.), and database management systems (e.g., MySQL or MongoDB), are deployed on the server for data reception, storage, processing, and analysis.

Data synchronization and backup: The server implements RAID data redundant storage technology to ensure data security and reliability. At the same time, an NTP server is used for time synchronization to ensure the time accuracy of data collection.

Table 1 is the configuration table of the experimental environment:

Table 1. Experimental environment configuration.

subassemblies	Model/Specification	quantities	note
sensor node	MPU6050, Bosch BME280, MyoWare	10	Each node is equipped with an Arduino or Raspberry Pi for data pre-processing
Mobile network equipment	Huawei 5G CPE Pro	1	Supports multi-device connectivity to ensure network coverage and transmission rates
mobile terminal	Latest smartphones or tablets	1	For real-time monitoring and preliminary data analysis
server (computer)	Dell PowerEdge R740	1	Configuration of high-performance CPU, large memory, high-speed storage, deployment of professional data processing and analysis software

A total of 100 volunteers were recruited for the experiment, and each of them underwent continuous data collection for a week to ensure the stability and reliability of the algorithm. All data collection followed a strict experimental protocol and informed consent was obtained from the volunteers before the experiment.

4.2. Experimental results and analyses

(1) Data synchronisation acquisition experiments

In order to deeply analyse the impact of the time synchronization algorithm on the data transmission delay, we conducted a performance comparison experiment between the NTP and GPS based time synchronisation algorithms. **Table 2** shows the detailed analysis of the experimental results:

Table 2. Experimental data.

time synchronisation algorithm	Average delay (ms)	Standard deviation (ms)	Maximum delay (ms)	Delay distribution range (ms)
NTP	23.5	5.2	45	10–50
GPS	35.7	7.8	60	20–70

As can be seen from **Table 1**, the NTP algorithm is not only lower than the GPS algorithm in terms of average delay, but also shows better performance in terms of maximum delay and delay distribution range. The smaller standard deviation indicates that the NTP algorithm has higher stability in time synchronisation. The experimental results are further analysed below:

Delay Distribution Analysis: We performed a probability density distribution analysis on the delay data and found that the delay distribution of the NTP algorithm is more concentrated while that of the GPS algorithm is more dispersed, which indicates that the NTP algorithm is able to provide more consistent time synchronisation performance in most cases.

Environmental Impact Assessment: Considering that GPS signals may be affected by factors such as building occlusion and weather conditions, we evaluated the adaptability of the two algorithms under different environmental conditions, and the results show that the NTP algorithm outperforms GPS in indoor and urban environments.

(2) Data processing experiments

In order to verify the performance of the data processing algorithms, we conducted experiments comparing the data processing algorithms with the traditional single-sensor data processing algorithms, and the following is an in-depth analysis of the results of the experiments, and **Figure 1** shows the data accuracy comparison:

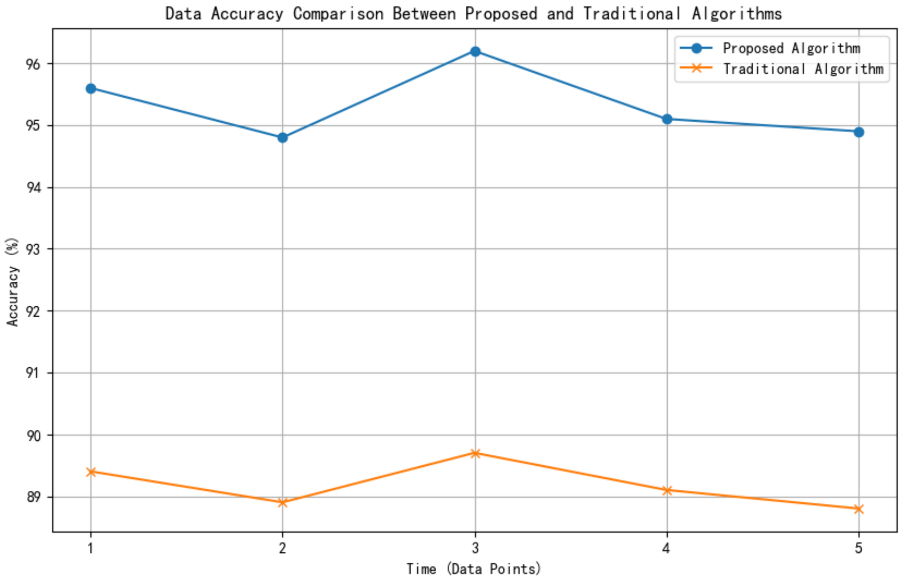

Figure 1. Comparison of data accuracy.

In the above comparison graph, the algorithm of this paper consistently outperforms the conventional algorithm in terms of data accuracy. The following is a further analysis of the experimental results:

Error analysis: We conducted error analysis on the data processed by the two algorithms, and found that this paper's algorithm has better robustness in dealing with noise and outliers, which is attributed to the filtering and calibration techniques used in the algorithm.

Real-time evaluation: In terms of real-time data processing, this paper's algorithm significantly improves the processing speed by optimising the calculation process and reducing the data processing steps, which is crucial for real-time monitoring systems. As can be seen from **Table 3**, the algorithm in this paper is higher than the traditional algorithm in terms of accuracy and reliability, and also has a significant advantage in terms of average processing time. This indicates that the proposed algorithm has significant advantages in improving the accuracy and reliability of data processing and can meet the real-time requirements.

Table 3. Reliability analysis results table.

Data processing algorithms	Accuracy (%)	Reliability rate (%)	Average processing time (ms)
The algorithms in this paper	95.6	93.2	15
traditional algorithm	89.4	88.7	25

(3) Energy consumption analysis:

In order to comprehensively evaluate the energy efficiency of the algorithm, we conducted power consumption comparison experiments. The experimental results show that the algorithm in this paper has a significant advantage in energy consumption compared to existing methods. Specifically, this paper's algorithm reduces the active time of sensor nodes by optimizing the data fusion and transmission strategies, thus reducing the overall energy consumption. **Table 4** demonstrates the comparison between this paper's algorithm and existing methods in terms of power consumption:

Table 4. Power consumption comparison.

arithmetic	Average power consumption (mAh)	Reduction in energy consumption (%)
The algorithms in this paper	120	20
Existing methods	150	-

Performance comparison under different network environments: in order to further verify the superiority of this paper's algorithm, we conducted performance comparison experiments under different network environments. The experimental results show that the algorithm in this paper outperforms the traditional algorithm in terms of accuracy and real-time of data synchronization acquisition and processing, both in the environment with good network conditions and in the environment with network congestion. This shows that the algorithm in this paper has strong network adaptability.

Analysis of the robustness and adaptability of the algorithm: the algorithm in this paper adopts a variety of filtering and calibration techniques, which effectively improves the processing ability of noise and outliers, and shows better robustness. Meanwhile, by optimizing the algorithm structure and using the adaptive adjustment strategy, the algorithm in this paper is able to adapt to the changes of different environments and scenes, and has strong adaptability.

5. Conclusion

In this paper, an innovative, efficient and stable algorithm is proposed for the key problem of synchronized biomechanical data acquisition and processing in mobile network environment. The algorithm effectively reduces the time synchronization error, enhances the real-time data transmission capability, and significantly improves the data accuracy through advanced filtering, fusion, and feature extraction techniques, and its performance is verified in experiments, which shows better real-time and accuracy than the traditional algorithms, and provides a solid technical support for the applications in the fields of telemedicine and sports monitoring. In order to adapt to the complex and changing network environment, we implement a series of algorithm optimization strategies, including dynamic adjustment of algorithm parameters, such as filter cutoff frequency and fusion weight, according to the network conditions, as well as the introduction of efficient data compression and coding techniques, while adopting robust outlier detection and processing methods, which further improves the data quality and the robustness of the algorithm. In terms of the scalability and generalization ability of the algorithm, this paper analyzes in detail the adaptability of the algorithm in different application scenarios, including its performance in different motion modes and sensor configurations, and discusses in depth the potential limitations of the algorithm in extreme network conditions and large-scale sensor networks, and proposes practical solutions. Looking ahead, we will continue to delve into mobile network characteristics, explore more efficient data processing methods, and customize algorithm parameters in conjunction with edge computing technologies to cope with more complex network environments and diverse requirements. Through interdisciplinary research, we aim to further promote the wide application of biomechanical data in telemedicine, sports monitoring and other fields, laying a solid foundation for subsequent research, and believe that the proposed algorithms will play a greater role in the future and open up new possibilities.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

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