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Article

Data acquisition and processing for IoT-based intelligent medical monitoring: Applications in biomechanics

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Abstract: With the rapid development of Internet of Things (IoT) technology, its integration into intelligent medical monitoring devices has significantly transformed the healthcare landscape. This integration not only enhances the functionality of medical monitoring equipment but also improves the real-time accuracy of data collection. This review comprehensively discusses the data acquisition and processing methods of intelligent medical monitoring devices based on IoT, with a particular focus on their applications in molecular and cellular biomechanics. In the context of biomechanics, IoT technology offers new perspectives and tools for biomechanics research. By accurately monitoring mechanical changes at the cellular and molecular levels, IoT technology enhances our understanding of biological systems, thereby providing a scientific foundation for the early diagnosis and treatment of diseases. For instance, by observing the mechanical responses of cells, we can gain insights into how cells sense and react to changes in their external environment. We summarize the current research progress related to IoT data acquisition and processing methods for these devices, analyze the advantages and limitations of existing technologies, and explore future development trends. The review seeks to foster technological innovation and practical applications within this field, ultimately enhancing the quality of medical care and improving the overall quality of life for patients.

Keywords: biomechanics; data acquisition; data processing; internet of things (IoT); intelligent medical monitoring; healthcare innovation

1. Introduction

Internet of Things (IoT) technology, regarded as the third revolutionary wave of the information industry, is transforming the convergence and interaction patterns of global networks through its unique intelligent sensing, recognition, and computing technologies [1]. At the core of IoT is the ability to connect physical devices to the Internet via embedded systems, enabling automated data collection, exchange, and analysis to optimize operational processes and enhance efficiency [2]. In this context, the application of IoT technology in the medical field is particularly compelling, especially regarding the data collection and processing capabilities of intelligent medical monitoring devices, the potential of which is gradually being explored and realized.

In the medical field, the application of IoT technology extends beyond mere data collection. It also encompasses the comprehensive analysis and utilization of this data to facilitate precision medicine and personalized treatment. Intelligent medical monitoring devices, which serve as crucial components of IoT technology in healthcare, significantly influence the efficiency and quality of medical services through their data collection and processing capabilities [3]. These devices can monitor patients' physiological parameters in real time, such as heart rate, blood pressure, and blood glucose levels [4–7]. Thereby providing essential information for clinical decision-making. However, ensuring the accuracy, timeliness, and safety of this data, as well as transforming it into actionable clinical insights, remains a pressing challenge in contemporary research.

At the molecular and cellular biomechanics level, the application of IoT technology offers new perspectives and tools for biomechanics research [8]. By accurately monitoring mechanical changes at the cellular and molecular levels, IoT technology enhances our understanding of biological systems, thereby providing a scientific foundation for the early diagnosis and treatment of diseases. For instance, by observing the mechanical responses of cells, we can gain insights into how cells sense and react to changes in their external environment. This understanding is crucial for studying cell signaling, tissue regeneration, and disease progression [9,10].

The aim of this review is to explore the application of IoT technologies for data acquisition and processing methods in smart medical monitoring devices, particularly in the field of molecular and cellular biomechanics. We will analyze how IoT technologies facilitate efficient data acquisition and processing, and how these technologies can enhance our understanding and application of biomechanical principles to improve clinical outcomes. Through this review, we aim to provide readers with a comprehensive overview of the current status and future directions of IoT technologies in smart medical monitoring devices, as well as how these technologies can be integrated with recent advancements in biomechanics to collectively advance biomedical science.

2. Research on data collection methods

2.1. Sensor technology

In the research and application of intelligent medical monitoring devices, sensor technology plays a crucial role [11]. As the core component of data acquisition, the research and development of sensors are directly linked to the performance of monitoring devices and the effectiveness of clinical applications.

2.1.1. Types of sensors

Driven by continuous innovation in the field of biomedical engineering, sensor technology has made remarkable advancements, particularly in smart medical monitoring devices, where the range of sensors for various physiological parameters is expanding. The design and application of these sensors offer robust technical support for precision medicine and personalized health management. A diverse array of sensors applicable to different physiological parameters, such as electrocardiogram (ECG) sensors, blood pressure sensors, and blood oxygen sensors, has been developed.

Cardiac sensors

ECG sensors are essential tools for monitoring cardiac activity and diagnosing cardiac diseases, such as arrhythmias, by capturing ECG signals [12]. With advancements in microelectronics technology, ECG sensors have achieved high-precision, low-power signal acquisition and have demonstrated significant potential in the field of mobile health monitoring [13].

Blood pressure sensor

Blood pressure sensors play a crucial role in the prevention and treatment of cardiovascular diseases, such as hypertension, by noninvasively monitoring changes in blood pressure [14]. For molecular and cellular biomechanics, sensors that can detect mechanical forces at the nanoscale are of particular interest. These sensors can be integrated into cell culture systems or implanted in vivo to monitor the mechanical environment of tissues and cells. For example, piezoelectric sensors can detect changes in cellular stiffness and contractility, providing real-time data on cellular biomechanical behavior. Current research is focused on enhancing the accuracy and comfort of these sensors for long-term monitoring. Significant advancements are being made in cuffless blood pressure monitoring technologies [15], which are anticipated to replace traditional blood pressure measurement methods in the near future, offering patients a more convenient monitoring experience.

Oxygen sensor

Oximetry sensors monitor blood oxygen saturation in real time, serving as a crucial tool for patients with respiratory diseases [16]. In recent years, optical-based oximetry sensors have garnered significant attention due to their noninvasive nature and ability to provide continuous monitoring [17].

Other sensors

In addition to the aforementioned sensors, temperature sensors [18] and blood glucose sensors [19] are also vital components of smart medical monitoring devices. Temperature sensors can monitor fluctuations in body temperature, which is essential for the early detection and management of febrile illnesses [20]. Conversely, blood glucose sensors play a critical role in enhancing the quality of life for diabetic patients, as they enable real-time monitoring of blood glucose levels, thereby assisting patients in better managing their health [21].

Together, these sensors create a sensor network for multiparameter monitoring, equipping healthcare professionals with a robust tool for comprehensively assessing a patient's health status. As technology continues to advance, sensors are evolving towards miniaturization, increased intelligence, and multifunctionality, which will further enhance the application of intelligent medical monitoring devices in clinical practice.

2.1.2. Sensor performance

The enhancement of sensor performance is undoubtedly one of the central topics in the research and development of intelligent medical monitoring devices [22]. Key performance indicators, such as sensitivity, stability, and anti-interference capability, are directly related to the accuracy and reliability of the collected data.

Consequently, these indicators have become essential criteria for evaluating sensor performance [23].

Sensitivity optimization

In the context of molecular and cellular biomechanics, the development of highly sensitive and specific sensors is essential for capturing subtle mechanical changes at the cellular level. These sensors can provide real-time data on cellular responses to mechanical stimuli, such as changes in cell shape, stiffness, and signaling pathways [24]. Innovations in materials science have led researchers to introduce novel nanomaterials, such as graphene [25] and carbon nanotubes [26], which possess a high surface area and exceptional electronic properties, significantly improving sensor sensitivity. These sensors can provide real-time data on cellular responses to mechanical stimuli. Furthermore, by employing surface functionalization techniques, researchers can further enhance the responsiveness of sensors to specific physiological parameters, enabling more accurate monitoring.

Stability improvement

Stability of sensors is crucial for ensuring reliable monitoring over time [27]. The application of microelectromechanical systems (MEMS) technology offers innovative solutions for the miniaturization and stabilization of sensors [28]. With MEMS technology, sensors can be miniaturized while preserving their mechanical and electrical stability, allowing them to maintain consistent performance across a range of environments, including extreme temperatures, humidity levels, and mechanical vibrations.

Enhanced anti-interference capability

In complex physiological monitoring environments, the anti-interference capability of sensors is essential [29]. Advances in digital signal processing technology have introduced innovative methods to enhance this capability [30]. Researchers have developed a variety of algorithms, including noise filtering, signal amplification, and pattern recognition, to eliminate or minimize the impact of external interference on sensor signals [31].

The enhancement of sensor performance depends on the interdisciplinary collaboration among various fields, including materials science, microelectronic engineering, and signal processing [32]. Researchers continually optimize sensor design through this collaboration, for instance, by integrating research on biocompatible materials to create sensors that are better suited for in vivo implantation [33]. Advances in microelectronic engineering technologies are employed to achieve high integration and low power consumption in sensors [34]. Additionally, advanced signal processing techniques are utilized to enhance the sensors' ability to interpret data in complex environments [35]. Through ongoing material innovation, technological integration, and algorithm optimization, the sensitivity, stability, and resistance to interference of sensors have significantly improved. This not only enhances the applicability of sensors in challenging environments but also provides more accurate and reliable data support for medical diagnosis and treatment.

2.1.3. Sensor integration

In the medical monitoring field, sensor integration technology has emerged as a focal point of research due to the increasing demand for multi-parameter monitoring. The essence of this technology is the integration of multiple sensors onto a single platform, enabling the simultaneous acquisition of various physiological parameters [36]. By consolidating multiple sensors, the synchronized collection of diverse parameters is achieved, thereby enhancing the comprehensiveness of data acquisition. For instance, the integration of force sensors with biochemical sensors can offer valuable insights into how mechanical forces influence cell signaling pathways and gene expression. The miniaturization of design and seamless integration are crucial for developing wearable or implantable devices that can monitor cellular biomechanics without disrupting normal physiological processes.

Miniaturized design and integration

Research in sensor integration begins with the challenge of miniaturized design. To achieve multi-parameter monitoring without disrupting the patient's daily activities, researchers have focused on developing miniaturized sensors [37]. These sensors facilitate the integration of multiple functions within a compact space by utilizing MEMS technology [38]. Miniaturized design necessitates not only a reduction in sensor size but also the maintenance of performance, which demands synergistic innovations in materials science and precision engineering technologies.

Low power circuit design

Integrated sensors cannot operate efficiently without the support of low-power circuits [39]. To ensure that the sensor module operates stably over extended periods, researchers have developed various low-power circuit designs. These designs encompass optimized power management circuits, low-power signal processing units, and energy recovery techniques [40]. With these advancements, integrated sensors can sustain data acquisition and transmission for prolonged durations while utilizing a limited energy supply.

Data fusion algorithms

Data fusion algorithms play a crucial role in multiparameter monitoring [41]. These algorithms can process data from various sensors, extract valuable information, reduce data redundancy, and enhance data accuracy. Researchers are developing advanced data fusion techniques, including time series analysis [42], pattern recognition [43], and machine learning algorithms [44], to facilitate more efficient data processing and provide deeper insights into health state analysis.

Energy efficiency

The design of integrated sensors must also prioritize energy efficiency [45]. This entails optimizing sensor operating modes, developing dormancy strategies, and managing energy allocation. For instance, overall energy consumption can be significantly reduced by intelligently activating the sensor's operating mode and conducting data acquisition only when necessary [46]. Furthermore, research has focused on the development of innovative energy storage technologies, such as flexible batteries [47] and supercapacitors [48], to support integrated sensor systems that function over extended periods.

Currently, researchers are developing wearable multiparameter sensor modules capable of continuously monitoring key physiological parameters, such as ECG, blood pressure, and blood oxygen levels [49,50]. These wearable devices are designed with ergonomics in mind to ensure patient comfort during daily activities. By integrating advanced sensor technology, these devices provide physicians with comprehensive, real-time information about the patient's health, thereby enhancing the accuracy of diagnoses and the effectiveness of treatments.

2.2. Communications technology

In the development and application of intelligent medical monitoring devices, IoT communication technology is essential for facilitating data collection and transmission.

2.2.1. Wireless communications

Wi-Fi technology

Wi-Fi technology, based on the IEEE 802.11 standard, has become an indispensable means of communication in smart medical monitoring devices. This technology is capable of providing data transfer rates of up to hundreds of megabits per second, which is crucial for transmitting large volumes of real-time data in environments such as hospitals [51]. The relatively wide coverage of Wi-Fi technology, typically extending up to hundreds of meters, enables it to meet the communication needs of large-scale medical facilities. In medical surveillance systems, Wi-Fi technology not only supports the transmission of high-definition video streams but also ensures rapid synchronization of medical data, thereby enhancing the efficiency of medical services.

Bluetooth technology

Bluetooth technology, a short-range wireless communication method, has particularly prominent applications in wearable medical devices. With the advancement of Bluetooth Low Energy (BLE) technology, Bluetooth devices can achieve rapid connections and data transmission with terminals such as smartphones and tablets while maintaining low power consumption [52]. Although the transmission rate and range of BLE technology are not as high as those of traditional Bluetooth, its lower energy consumption and compact size make it the preferred communication solution for wearable medical devices [53]. Furthermore, the maturity and widespread market acceptance of Bluetooth technology facilitate the proliferation of smart medical monitoring devices.

ZigBee technology

ZigBee technology, characterized by its low-speed, short-range transmission, and cost-effectiveness, plays a significant role in healthcare monitoring networks [54]. This technology supports self-organizing network capabilities, facilitating the efficient deployment of numerous sensor nodes within healthcare environments. These nodes can collectively form a sensor network that offers extensive coverage and numerous nodes for real-time monitoring of patients' physiological parameters [55]. Another notable advantage of ZigBee technology is its low power consumption, which is crucial for medical monitoring devices that require prolonged operation and are not easily serviced for battery replacement.

2.2.2. Wired communications

Although wireless communication technology is widely utilized in intelligent medical monitoring devices, wired communication technology continues to play an indispensable role in certain specific scenarios, particularly in environments that demand high real-time data transmission. For instance, serial ports and USB connections are well-suited for applications with stringent real-time requirements.

Serial communications technology

Serial communication, a traditional wired data transmission method, facilitates the exchange of data through a serial communication interface. Its high stability and resistance to interference provide significant advantages in data transmission scenarios that require precise control [56,57]. In intelligent medical monitoring devices, serial communication is commonly employed for real-time monitoring [58] and hardware control [59]. For instance, in applications such as ECG monitoring and blood pressure monitoring, serial communication ensures data accuracy and transmission stability while minimizing errors caused by signal interference or attenuation. Furthermore, for medical devices that necessitate precise control, such as surgical robots and precision testing instruments, serial communication offers reliable data transmission, thereby ensuring the normal operation of these devices.

USB communication technology

USB (Universal Serial Bus) communication is a widely used computer interface that plays a crucial role in data transmission between medical devices and computers, owing to its high data transfer speed and excellent compatibility [60]. The advantages of USB communication technology include: 1) USB interfaces can provide data transfer rates of up to several tens of megabits per second, which is essential for transmitting large medical data files [61]. 2) The plug-and-play functionality of USB communication simplifies the process of connecting devices, thereby enhancing the efficiency of medical personnel. 3) The USB interface supports the connection of multiple devices, facilitating the seamless integration of medical monitoring devices with other medical information systems [62].

The application of wired communication technology in intelligent medical monitoring equipment ensures stability and real-time data transmission, particularly in environments with stringent requirements for data accuracy and transmission speed. As medical informatization continues to advance, wired communication technology will remain crucial in intelligent medical monitoring devices, complementing wireless communication technology to collectively enhance the development of medical monitoring technology.

2.2.3. Low-power communications

Low-power communication technologies are particularly crucial in the realm of intelligent medical monitoring devices, especially for those that rely on battery power. These technologies not only facilitate the long-term operation of the devices but also ensure reliable data transmission in complex environments [63].

Technologies such as LoRa and NB-IoT are well-suited for battery-powered medical monitoring devices.

LoRa technology

LoRa (Long Range) technology, which is based on the principles of spread-spectrum communication, is a low-power, long-range wireless communication solution [64]. Operating in the sub-GHz frequency band, LoRa technology enables stable data transmission even in remote areas with poor signal coverage—a feature that is particularly crucial for medical monitoring devices. Additionally, LoRa devices exhibit extremely low power consumption, resulting in longer lifespans and reduced maintenance requirements for battery-powered medical monitoring equipment [65]. Furthermore, LoRa technology supports connectivity for a large number of devices, making it highly advantageous for establishing extensive medical surveillance networks that can accommodate various application scenarios, such as hospitals and homes.

NB-IoT technology

Narrowband Internet of Things (NB-IoT) technology is a low-power, wide-coverage communication solution specifically designed for the Internet of Things [66]. The application of NB-IoT technology in medical monitoring equipment exhibits several key characteristics. First, the narrowband nature of NB-IoT enables stable communication while consuming minimal power, making it particularly suitable for frequent small packet transmissions in medical monitoring devices [67]. Second, NB-IoT technology offers extensive coverage over large geographic areas, including basements and remote locations, which is essential for ensuring the continuity and reliability of medical monitoring data. Most importantly, NB-IoT technology provides a stable network connection that minimizes latency and interruptions in data transmission, a critical factor for monitoring patient conditions that require real-time oversight [68].

The application of low-power communication technology in intelligent medical monitoring devices significantly enhances the long-term operation of these devices and ensures stable data transmission. The distinct advantages of LoRa and NB-IoT technologies allow medical monitoring devices to achieve efficient and reliable data collection and transmission across various environments and requirements.

3. Research on data-processing methods

In the application of intelligent medical monitoring equipment, data processing is a crucial component that directly impacts the accuracy and practicality of the final monitoring results. Data processing techniques are essential for extracting meaningful information from the complex mechanical signals generated by cells and tissues in biomechanical applications.

3.1. Data pre-processing

Data preprocessing is a crucial initial stage in the data processing workflow of intelligent medical monitoring equipment. Its primary objective is to enhance data quality and ensure the accuracy and effectiveness of subsequent analyses and processing [69]. Data preprocessing primarily involves operations such as denoising, filtering, and normalization, all aimed at improving data quality and providing a reliable foundation for further processing. In biomechanical studies, denoising and filtering are crucial for maintaining the integrity of mechanical signals. For instance, low-pass filtering can effectively eliminate high-frequency noise from force measurements, while normalization ensures that data from various sensors or experiments remain comparable.

3.1.1. Denoising

During the acquisition of medical monitoring data, environmental interference and the inherent noise of the equipment often affect the data. This interference can obscure genuine physiological signals and compromise the final monitoring results. Denoising is the initial step in data preprocessing, aimed at minimizing the impact of noise on data quality. Specific methods for denoising include median filtering and Kalman filtering [70]. Median filtering is a nonlinear technique that effectively suppresses impulse and random noise while preserving the edge characteristics of the signal. It is particularly suitable for data denoising that requires high real-time performance [71]. In contrast, Kalman filtering is an optimal estimation algorithm that recursively estimates noise-contaminated data through two steps: prediction and updating. This process filters out noise and extracts the clean signal [72].

3.1.2. Filtering operation

Filtering operations play a crucial role in data preprocessing by eliminating irrelevant information and preserving physiological signals that are essential for diagnosis. Common filtering methods include low-pass filtering, high-pass filtering, and band-pass filtering [73]. Low-pass filters permit low-frequency signals to pass through while attenuating high-frequency signals, making them effective for removing high-frequency noise, such as power line interference [74]. In contrast, high-pass filters allow high-frequency signals to pass while eliminating low-frequency noise, such as motion artifacts [75]. Band-pass filters selectively permit signals within a specific frequency range to pass while suppressing signals outside that range, making them suitable for extracting physiological signals within designated frequency bands [76].

3.1.3. Normalization process

Normalization is a crucial aspect of data preprocessing that enhances the comparability of data collected from various sensors by adjusting the data scale, thereby facilitating subsequent data analysis. Linear normalization can efficiently standardize the data scale by mapping it linearly to the $[0, 1]$ or $[-1, 1]$ interval. Additionally, the data can be centered by subtracting the mean and then scaled by dividing by the standard deviation, resulting in a dataset with a mean of zero and a unit variance, which is ideal for further statistical analysis [77].

Data preprocessing is an essential component of the data processing workflow for intelligent medical monitoring equipment. Through operations such as denoising, filtering, and normalization, data preprocessing not only enhances data quality but also establishes a robust foundation for subsequent complex analyses. With the ongoing advancements in signal processing technology, data preprocessing methods are becoming increasingly efficient and precise, thereby providing substantial support for the application of intelligent medical monitoring devices in clinical settings.

3.2. Data compression and fusion

With the widespread use of intelligent medical monitoring devices, the vast amount of data generated presents new challenges for data processing efficiency. Research into data compression and fusion technologies has become a crucial approach to enhancing data processing efficiency.

3.2.1. Data compression technology

Data compression techniques aim to alleviate the demands of data transmission and storage while ensuring the integrity of the information represented by the data. By leveraging the sparsity of signals, compressed sensing techniques can reconstruct signals at a sampling rate significantly lower than the Nyquist rate, thereby substantially reducing the volume of data [78]. This approach is particularly effective for physiological signals characterized by sparsity, such as ECG and electroencephalogram (EEG) signals. The wavelet transform is a time-frequency localized analysis method that decomposes a signal into wavelet coefficients across various frequencies [79]. By applying thresholding, redundant information can be eliminated, facilitating data compression. The wavelet transform effectively reduces data size while preserving the essential features of the signal.

3.2.2. Data fusion technology

Data fusion techniques enhance the accuracy and completeness of information by integrating data from various sensors or different time points [80]. There could be a more comprehensive understanding of cellular behavior in terms of molecular and cellular biomechanics. For instance, combining data from force and imaging sensors can yield both quantitative and qualitative insights into cellular biomechanics. In the context of medical surveillance, applications of data fusion techniques include weighted averaging, Kalman filtering, and multi-sensor data fusion algorithms.

The weighted averaging method generates a composite value by assigning varying weights to data collected from different sensors. This method is straightforward and easy to implement, making it suitable for scenarios where the consistency of sensor data is high [81]. Kalman filtering, on the other hand, is a recursive optimal estimation algorithm that integrates predicted and observed values to provide an optimal estimate of the system state [82]. In the context of multi-sensor data fusion, Kalman filtering effectively reduces noise and enhances data quality. Beyond the traditional Kalman filter, researchers have developed a range of multi-sensor data fusion algorithms, including neural networks and support vector machines, which can address more complex data relationships and improve the overall fusion effectiveness [83].

3.3. Data analysis and mining

Data analysis and mining are essential technologies for extracting valuable information from medical surveillance data, which is crucial for the early detection, diagnosis, and treatment of diseases. The primary methods of data analysis and mining include time-domain analysis, frequency-domain analysis, machine learning, and deep learning.

3.3.1. Time domain analysis

Time-domain analysis serves as the foundation for data analysis, revealing the time-domain characteristics of signals through direct statistical examination of raw data. In the realm of medical monitoring, the primary methods of time-domain analysis include the calculation of basic statistical parameters and the extraction of waveform features [84]. Statistical parameter calculations, such as mean, variance, standard deviation, and root mean square, reflect the stability and volatility of the signal, providing essential data for subsequent signal identification and disease diagnosis [85]. Waveform feature extraction, exemplified by the time-domain analysis of heart rate variability, allows for the assessment of inter-beat interval variability in ECG signals [86]. This information is crucial for evaluating autonomic nervous system activity and diagnosing cardiovascular diseases.

3.3.2. Frequency domain analysis

Frequency domain analysis reveals the frequency components and dynamics of a signal by transforming the data into the frequency domain [87]. In the context of medical surveillance data, the primary techniques for frequency domain analysis include the Fourier transform and the wavelet transform. The Fourier transform converts a time-domain signal into a frequency-domain representation, thereby facilitating the analysis of the signal's frequency distribution [88]. In the analysis of ECG signals, the Fourier transform is instrumental in identifying the frequency domain features associated with arrhythmias. Conversely, the wavelet transform possesses the unique property of time-frequency localization, allowing for the analysis of frequency components across different time scales. The wavelet transform demonstrates distinct advantages when addressing non-stationary physiological signals [89].

3.3.3. Machine learning and deep learning

Machine learning and deep learning techniques are increasingly utilized in the analysis of medical surveillance data, enabling intelligent analysis and prediction of complex datasets through the construction of data models. Specific applications include classification, regression, cluster analysis, and deep learning models [90]. Machine learning algorithms, such as support vector machines (SVM) and random forests (RF), can be employed for the classification and regression analysis of diseases, thereby supporting clinical decision-making. Clustering algorithms, including K-means and hierarchical clustering, can uncover natural groupings within data, which is crucial for exploring unknown disease patterns and patient categorization [91]. Deep learning models, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), offer significant advantages in processing time series data [92]. For instance, CNNs excel in classifying ECG images, while RNNs are particularly effective in analyzing sequence-dependent physiological signals.

4. Challenges and prospects

The development of low-power, high-sensitivity sensors is essential for the long-term monitoring of the mechanical properties of cell mechanics. Furthermore, data security and privacy protection are becoming increasingly critical, particularly when handling sensitive biomechanical data. Robust encryption techniques and stringent access control measures must be implemented during data transmission and processing. Despite the significant advancements in the research of IoT data acquisition and processing methods for smart medical monitoring devices, several challenges persist in practical applications, hindering the widespread deployment and comprehensive development of this technology. One of the primary concerns is achieving a balance between sensor performance and power consumption in the design of these devices. High-performance sensors typically come with increased power consumption, which restricts the portability and longevity of the device. To tackle this issue, researchers have sought to enhance sensor performance through.

Low-power sensor technology and dynamic power management are essential components in the development of modern medical monitoring devices. Additionally, with the advancement of IoT technology, data security and privacy protection have emerged as increasingly critical issues. In medical monitoring devices, patients' physiological data is highly sensitive; therefore, robust encryption techniques and stringent access control measures must be implemented during data transmission and processing. Furthermore, to enhance the overall performance of intelligent medical monitoring devices, system integration and optimization are crucial. This process involves the collaborative efforts of various components, including data acquisition, transmission, and processing, as well as the design of system architecture and performance optimization.

With the continuous advancement of IoT technology, data acquisition and processing methods for smart medical monitoring devices are anticipated to be realized. The development of more sensitive, stable, and low-power sensors is essential to meet the demands of long-term real-time monitoring. Additionally, it is crucial to establish a more robust data security protection system to safeguard patient privacy through technological innovation. Furthermore, the utilization of artificial intelligence and machine learning technologies will facilitate the integrated and intelligent management of data acquisition, transmission, and processing.

5. Conclusion

Compared to some existing studies, this review not only addresses a single technology or application but also systematically summarizes the integrated application of multiple data acquisition and processing methods in IoT smart medical monitoring devices, particularly in the field of molecular and cellular biomechanics. This review emphasizes the multi-protocol fusion of wireless IoT technologies, which significantly enhances the flexibility and scalability of these devices. In current research, data processing and fusion predominantly rely on a single tool or platform, such as Apache NiFi or Kafka. In contrast, this review further investigates the integration of multiple data processing tools, including the co-optimization of data preprocessing, compression, and fusion. For instance, by combining edge computing with AI models, devices can perform preliminary data processing locally, thereby reducing dependence on cloud resources. This optimization not only improves data processing efficiency but also decreases system latency. Compared to the existing literature, this review not only summarizes current technologies but also offers insights into future trends, such as the development of low-power sensor technologies, enhancements in data encryption and access control, and optimizations in system architecture. These forward-looking insights provide clear directions for researchers and technology developers, fostering continuous innovation in smart medical monitoring devices.

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References

1. Sanislav T, Mois GD, Zeadally S, et al. Energy Harvesting Techniques for Internet of Things (IoT). IEEE Access. 2021; 9: 39530-39549. doi: 10.1109/access.2021.3064066
2. Islam SMR, Lloret J, Zikria YB. Internet of Things (IoT)-Based Wireless Health: Enabling Technologies and Applications. Electronics. 2021; 10(2): 148. doi: 10.3390/electronics10020148
3. Hussain AA, Dawood BA. A survey on IoT-cloud task in healthcare system. The Journal of Supercomputing. 2024; 81(1). doi: 10.1007/s11227-024-06629-1
4. Guk K, Han G, Lim J, et al. Evolution of Wearable Devices with Real-Time Disease Monitoring for Personalized Healthcare. Nanomaterials. 2019; 9(6): 813. doi: 10.3390/nano9060813
5. Ota H, Chao M, Gao Y, et al. 3D Printed "Earable" Smart Devices for Real-Time Detection of Core Body Temperature. ACS Sensors. 2017; 2(7): 990-997. doi: 10.1021/acssensors.7b00247
6. Lebedinskii KM, Kovalenko AN, Kurapeev IS, et al. Physical and Physiological Problems of Medical Monitoring. Technical Physics. 2020; 65(9): 1343-1359. doi: 10.1134/s1063784220090212
7. Lu C, Wang X, Jia Q, et al. 3D printed mechanical robust cellulose derived liquid-free ionic conductive elastomer for multifunctional electronic devices. Carbohydrate Polymers. 2024; 324: 121496. doi: 10.1016/j.carbpol.2023.121496
8. Cereatti A, Gurchiek R, Mündermann A, et al. ISB recommendations on the definition, estimation, and reporting of joint kinematics in human motion analysis applications using wearable inertial measurement technology. Journal of Biomechanics. 2024; 173: 112225. doi: 10.1016/j.jbiomech.2024.112225
9. Yang L, Sinsurin K, Shen F, et al. Biomechanical changes in lower extremity in individuals with knee osteoarthritis in the past decade: A scoping review. Heliyon. 2024; 10(11): e32642. doi: 10.1016/j.heliyon.2024.e32642
10. Fandaros M, Kwok C, Wolf Z, et al. Patient-Specific Numerical Simulations of Coronary Artery Hemodynamics and Biomechanics: A Pathway to Clinical Use. Cardiovascular Engineering and Technology. 2024; 15(5): 503-521. doi: 10.1007/s13239-024-00731-4
11. Zarei M. Portable biosensing devices for point-of-care diagnostics: Recent developments and applications. TrAC Trends in Analytical Chemistry. 2017; 91: 26-41. doi: 10.1016/j.trac.2017.04.001
12. Qin J. A design and optimization of CMOS ECG amplifier applied to medical monitoring system. Highlights in Science, Engineering and Technology. 2023; 32: 56-64. doi: 10.54097/hset.v32i.4939

13. Correia Pinheiro E, Postolache OA, Silva Girão P. Implementation of Compressed Sensing in Telecardiology Sensor Networks. International Journal of Telemedicine and Applications. 2010; 2010: 1-12. doi: 10.1155/2010/127639
14. Ahmadpour A, Yetisen AK, Tasoglu S. Piezoelectric Metamaterial Blood Pressure Sensor. ACS Applied Electronic Materials. 2023; 5(6): 3280-3290. doi: 10.1021/acsaelm.3c00344
15. Miao F, Liu ZD, Liu JK, et al. Multi-Sensor Fusion Approach for Cuff-Less Blood Pressure Measurement. IEEE Journal of Biomedical and Health Informatics. 2020; 24(1): 79-91. doi: 10.1109/jbhi.2019.2901724
16. Saffati G, Wiatrowski A, Khera M, et al. (136) Development and Evaluation of a Novel Penile Blood Oxygen Sensor for Assessing Tissue Oxygenation. The Journal of Sexual Medicine. 2024; 21(Supplement_1). doi: 10.1093/jsxmed/qdae001.130
17. Kannan Loganathan P, O'Shea JE, Harikumar C, et al. Effect of opaque wraps for pulse oximeter sensors: randomised cross-over trial. Archives of Disease in Childhood - Fetal and Neonatal Edition. 2020; 106(1): 57-61. doi: 10.1136/archdischild-2020-319049
18. Liu R, He L, Cao M, et al. Flexible Temperature Sensors. Frontiers in Chemistry. 2021; 9. doi: 10.3389/fchem.2021.539678
19. Litvinova O, Eitenberger M, Bilir A, et al. Patent analysis of digital sensors for continuous glucose monitoring. Frontiers in Public Health. 2023; 11. doi: 10.3389/fpubh.2023.1205903
20. Arman Kuzubasoglu B, Kursun Bahadir S. Flexible temperature sensors: A review. Sensors and Actuators A: Physical. 2020; 315: 112282. doi: 10.1016/j.sna.2020.112282
21. Nascimento RAS, Mulato M. Microelectronic sensor for continuous glucose monitoring. Applied Physics A. 2019; 125(3). doi: 10.1007/s00339-019-2455-6
22. An BW, Shin JH, Kim SY, et al. Smart Sensor Systems for Wearable Electronic Devices. Polymers. 2017; 9(8): 303. doi: 10.3390/polym9080303
23. Abbas N, Yu F, Fan Y. Intelligent Video Surveillance Platform for Wireless Multimedia Sensor Networks. Applied Sciences. 2018; 8(3): 348. doi: 10.3390/app8030348
24. Jin J, Zhang C, Zhao J, et al. An adaptive bionic sensor: enhancing ankle joint tracking with high sensitivity and superior cushioning performance. Chemical Engineering Journal. 2024; 500: 157332. doi: 10.1016/j.cej.2024.157332
25. Justino CIL, Gomes AR, Freitas AC, et al. Graphene based sensors and biosensors. TrAC Trends in Analytical Chemistry. 2017; 91: 53-66. doi: 10.1016/j.trac.2017.04.003
26. Schroeder V, Savagatrup S, He M, et al. Carbon Nanotube Chemical Sensors. Chemical Reviews. 2018; 119(1): 599-663. doi: 10.1021/acs.chemrev.8b00340
27. Wu H, Chai S, Zhu L, et al. Wearable fiber-based visual strain sensors with high sensitivity and excellent cyclic stability for health monitoring and thermal management. Nano Energy. 2024; 131: 110300. doi: 10.1016/j.nanoen.2024.110300
28. Sripriya T, Juliette AA. Theoretical analysis and comparative study of assorted diaphragm primarily based Micro Electro Mechanical System (MEMS) optical pressure sensors. Expert Systems with Applications. 2024; 245: 122993. doi: 10.1016/j.eswa.2023.122993
29. Chen Y, Feng T, Li C, et al. Comprehensive and Robust Anti-Jamming Dual-Electrode Pair Sensor. Small. 2024; 20(51). doi: 10.1002/smll.202406739
30. Cao X, Jiang K. Design of intelligent terminal app for digital manufacturing technology based on virtual reality and wireless sensor network technology. The International Journal of Advanced Manufacturing Technology; 2024.
31. Khalili M, GholamHosseini H, Lowe A, et al. Motion artifacts in capacitive ECG monitoring systems: a review of existing models and reduction techniques. Medical & Biological Engineering & Computing. 2024; 62(12): 3599-3622. doi: 10.1007/s11517-024-03165-1
32. Jin Z, Yim W, Retout M, et al. Colorimetric sensing for translational applications: from colorants to mechanisms. Chemical Society Reviews. 2024; 53(15): 7681-7741. doi: 10.1039/d4cs00328d
33. Mei X, Ye D, Zhang F, et al. Implantable application of polymer-based biosensors. Journal of Polymer Science. 2021; 60(3): 328-347. doi: 10.1002/pol.20210543
34. Baek S, Jo Y, Lee Y, et al. Design and Integration of Organic Printed Thin-Film Transistor-Based Soft Biosensors for Wearable Applications. ACS Applied Electronic Materials. 2024; 6(11): 7657-7678. doi: 10.1021/acsaelm.4c01632
35. Zampolli S, Elmi I, Bruschi P, et al. An ASIC-based system-in-package MEMS gas sensor with impedance spectroscopy readout and AI-enabled identification capabilities. Sensors and Actuators B: Chemical. 2025; 424: 136924. doi: 10.1016/j.snb.2024.136924

36. Cubells-Beltrán MD, Reig C, Madrenas J, et al. Integration of GMR Sensors with Different Technologies. Sensors. 2016; 16(6): 939. doi: 10.3390/s16060939
37. Zaras I, Sokal M, Jarczewska M. Studies on the ssDNA-Based Biosensor Regeneration and Miniaturization for Electrochemical Detection of miRNAs. Journal of The Electrochemical Society. 2024; 171(11): 117520. doi: 10.1149/1945-7111/ad91e5
38. Chen J, Li J, Li Y, et al. Design and Fabrication of a Miniaturized GMI Magnetic Sensor Based on Amorphous Wire by MEMS Technology. Sensors. 2018; 18(3): 732. doi: 10.3390/s18030732
39. Chatterjee B, Mohseni P, Sen S. Bioelectronic Sensor Nodes for the Internet of Bodies. Annual Review of Biomedical Engineering. 2023; 25(1): 101-129. doi: 10.1146/annurev-bioeng-110220-112448
40. Kwon SK, Kim JN, Byun HG, et al. Low-power and cost-effective readout circuit design for compact semiconductor gas sensor systems. Electrochemistry Communications. 2024; 169: 107834. doi: 10.1016/j.elecom.2024.107834
41. Rivera Velázquez JM, Mailly F, Nouet P. System-level simulations of multi-sensor systems and data fusion algorithms. Microsystem Technologies. 2018; 28(6): 1399-1408. doi: 10.1007/s00542-018-4204-8
42. Habash O, Mizouni R, Singh S, et al. Gaussian process-based online sensor selection for source localization. Internet of Things. 2024; 28: 101388. doi: 10.1016/j.iot.2024.101388
43. Song Y, Li M, Wang F, et al. Contact Pattern Recognition of a Flexible Tactile Sensor Based on the CNN-LSTM Fusion Algorithm. Micromachines. 2022; 13(7): 1053. doi: 10.3390/mi13071053
44. Pan N. A sensor data fusion algorithm based on suboptimal network powered deep learning. Alexandria Engineering Journal. 2022; 61(9): 7129-7139. doi: 10.1016/j.aej.2021.12.058
45. Wang K, Zhang L. Integrated design of high-speed permanent-magnet machines considering sensorless operation. IEEJ Transactions on Electrical and Electronic Engineering. 2018; 13(8): 1189-1195. doi: 10.1002/tee.22682
46. Landi G, Avallone G, Barone C, et al. Design of an Environmental Sensor Board for Energy Harvesting: Integration of Conventional and Eco-friendly Sensors with Power Generation Sources. Electronics. 2024; 13(19): 3801.
47. Sheng H, Ma Y, Zhang H, et al. Integration of Supercapacitors with Sensors and Energy-Harvesting Devices: A Review. Advanced Materials Technologies. 2024; 9(21). doi: 10.1002/admt.202301796
48. Lee J, Kim S, Kim JW, et al. Self-Healing and Antifreezing/Antidrying Conductive Eutectohydrogel-Based Biosignal Monitoring Multisensors with Integrated Supercapacitor. Small. 2024; 21(3). doi: 10.1002/smll.202409365
49. Hu X, Cao J, Wu H. A wearable device for collecting multi-signal parameters of newborn. Computer Communications. 2020; 154: 269-277. doi: 10.1016/j.comcom.2020.02.082
50. Ates HC, Nguyen PQ, Gonzalez-Macia L, et al. End-to-end design of wearable sensors. Nature Reviews Materials. 2022; 7(11): 887-907. doi: 10.1038/s41578-022-00460-x
51. Bassoli M, Bianchi V, Munari ID. A Plug and Play IoT Wi-Fi Smart Home System for Human Monitoring. Electronics. 2018; 7(9): 200. doi: 10.3390/electronics7090200
52. Yu L, Nazir B, Wang Y. Intelligent power monitoring of building equipment based on Internet of Things technology. Computer Communications. 2020; 157: 76-84. doi: 10.1016/j.comcom.2020.04.016
53. Li J, Ma Q, Chan AHS, et al. Health monitoring through wearable technologies for older adults: Smart wearables acceptance model. Applied Ergonomics. 2019; 75: 162-169. doi: 10.1016/j.apergo.2018.10.006
54. Zhu J, Fu J, Sun Y, et al. Design of Intelligent Safety Monitoring System for Power Supply Bureau Based on ZigBee Technology and Information Fusion. Journal of Physics: Conference Series. 2020; 1486(2): 022017. doi: 10.1088/1742-6596/1486/2/022017
55. Vitazkova D, Kosnacova H, Turonova D, et al. Transforming Sleep Monitoring: Review of Wearable and Remote Devices Advancing Home Polysomnography and Their Role in Predicting Neurological Disorders. Biosensors. 2025; 15(2): 117. doi: 10.3390/bios15020117
56. Huang C, Sun CC, Duan N, et al. Smart Meter Pinging and Reading Through AMI Two-Way Communication Networks to Monitor Grid Edge Devices and DERs. IEEE Transactions on Smart Grid. 2022; 13(5): 4144-4153. doi: 10.1109/tsg.2021.3133952
57. Wang Q, Li H, Wang H, et al. A Remote Calibration Device Using Edge Intelligence. Sensors. 2022; 22(1): 322. doi: 10.3390/s22010322
58. Su C, Chen W. Design of Remote Real-Time Monitoring and Control Management System for Smart Home Equipment Based on Wireless Multihop Sensor Network. Zeng W, ed. Journal of Sensors. 2022; 2022: 1-10. doi: 10.1155/2022/6228440

59. Si Y, Korada N, Ayyanar R, et al. A High Performance Communication Architecture for a Smart Micro-Grid Testbed Using Customized Edge Intelligent Devices (EIDs) With SPI and Modbus TCP/IP Communication Protocols. IEEE Open Journal of Power Electronics. 2021; 2: 2-17. doi: 10.1109/ojpel.2021.3051327
60. Rodríguez-Ríos A, Espinoza-Téllez G, Martínez-Ezquerro JD, et al. Information and Communication Technology, Mobile Devices, and Medical Education. Journal of Medical Systems. 2020; 44(4). doi: 10.1007/s10916-020-01559-w
61. Yang LQ, Ruan SJ, Cheng KH, et al. Model-Based Deep Encoding Based on USB Transmission for Modern Edge Computing Architectures. IEEE Access. 2020; 8: 112553-112561. doi: 10.1109/access.2020.3002844
62. Ayub MF, Saleem MA, Altaf I, et al. Fuzzy extraction and PUF based three party authentication protocol using USB as mass storage device. Journal of Information Security and Applications. 2020; 55: 102585. doi: 10.1016/j.jisa.2020.102585
63. Joh H, Ryoo I. A hybrid Wi-Fi P2P with bluetooth low energy for optimizing smart device’s communication property. Peer-to-Peer Networking and Applications. 2014; 8(4): 567-577. doi: 10.1007/s12083-014-0276-0
64. Islam R, Rahman MdW, Rubaiat R, et al. LoRa and server-based home automation using the internet of things (IoT). Journal of King Saud University - Computer and Information Sciences. 2022; 34(6): 3703-3712. doi: 10.1016/j.jksuci.2020.12.020
65. Faye I, Fam PA, Ndiaye ML. Energy Consumption of IoT Devices: An Accurate Evaluation to Better Predict Battery Lifetime. Radio Science. 2022; 57(12). doi: 10.1029/2021rs007423
66. Sultania AK, Mahfoudhi F, Famaey J. Real-Time Demand Response Using NB-IoT. IEEE Internet of Things Journal. 2020; 7(12): 11863-11872. doi: 10.1109/jiot.2020.3004390
67. Boni A, Bianchi V, Ricci A, et al. NB-IoT and Wi-Fi Technologies: An Integrated Approach to Enhance Portability of Smart Sensors. IEEE Access. 2021; 9: 74589-74599. doi: 10.1109/access.2021.3082006
68. Martiradonna S, Piro G, Boggia G. On the Evaluation of the NB-IoT Random Access Procedure in Monitoring Infrastructures. Sensors. 2019; 19(14): 3237. doi: 10.3390/s19143237
69. Xia Y, Chen J, Lu X, et al. Big traffic data processing framework for intelligent monitoring and recording systems. Neurocomputing. 2016; 181: 139-146. doi: 10.1016/j.neucom.2015.07.140
70. Talaat M, Alsayyari AS, Alblawi A, et al. Hybrid-cloud-based data processing for power system monitoring in smart grids. Sustainable Cities and Society. 2020; 55: 102049. doi: 10.1016/j.scs.2020.102049
71. Zhang N, Wu C, Wu Y, et al. An improved target tracking algorithm and its application in intelligent video surveillance system. Multimedia Tools and Applications. 2018; 79(23-24): 15965-15983. doi: 10.1007/s11042-018-6871-y
72. Zhang Q, Pan S. An AI-Augmented Kalman Filter Approach to Monitoring Network Traffic Matrix. IEEE Transactions on Network Science and Engineering. 2024; 11(3): 2426-2437. doi: 10.1109/tnse.2023.3297660
73. R R, S M. Frequency response masking based FIR filter using approximate multiplier for bio-medical applications. Sādhanā. 2019; 44(11). doi: 10.1007/s12046-019-1186-x
74. Pérez-Bailón J, Calvo B, Medrano N. A CMOS Low Pass Filter for SoC Lock-in-Based Measurement Devices. Sensors. 2019; 19(23): 5173. doi: 10.3390/s19235173
75. Lin WC, Wang JW. Edge detection in medical images with quasi high-pass filter based on local statistics. Biomedical Signal Processing and Control. 2018; 39: 294-302. doi: 10.1016/j.bspc.2017.08.011
76. Yuan H, Ma L, Yuan Z, et al. On-Chip Cascaded Bandpass Filter and Wavelength Router Using an Intelligent Algorithm. IEEE Photonics Journal. 2021; 13(4): 1-8. doi: 10.1109/jphot.2021.3100357
77. Bhadoria RS, Bajpai D. Stabilizing Sensor Data Collection for Control of Environment-Friendly Clean Technologies Using Internet of Things. Wireless Personal Communications. 2019; 108(1): 493-510. doi: 10.1007/s11277-019-06414-x
78. Cormane J, de O. Nascimento FA. Spectral Shape Estimation in Data Compression for Smart Grid Monitoring. IEEE Transactions on Smart Grid. 2016; 7(3): 1214-1221. doi: 10.1109/tsg.2015.2500359
79. Landau-Feibish S, Liu Z, Rexford J. Compact Data Structures for Network Telemetry. ACM Computing Surveys. 2025; 57(8): 1-31. doi: 10.1145/3716819
80. Li X, Yu Q, Alzahrani B, et al. Data Fusion for Intelligent Crowd Monitoring and Management Systems: A Survey. IEEE Access. 2021; 9: 47069-47083. doi: 10.1109/access.2021.3060631
81. King RC, Villeneuve E, White RJ, et al. Application of data fusion techniques and technologies for wearable health monitoring. Medical Engineering & Physics. 2017; 42: 1-12. doi: 10.1016/j.medengphy.2016.12.011
82. Jan MA, Zhang W, Khan F, et al. Lightweight and smart data fusion approaches for wearable devices of the Internet of Medical Things. Information Fusion. 2024; 103: 102076. doi: 10.1016/j.inffus.2023.102076

83. Ghosh S, Manna D, Chatterjee A, et al. Remote Appliance Load Monitoring and Identification in a Modern Residential System With Smart Meter Data. IEEE Sensors Journal. 2021; 21(4): 5082-5090. doi: 10.1109/jsen.2020.3035057
84. Zong X, Zhang C, Wu D. Research on Data Mining of Sports Wearable Intelligent Devices Based on Big Data Analysis. Discrete Dynamics in Nature and Society. 2022; 2022(1). doi: 10.1155/2022/3723269
85. Ma Z, Xie J, Li H, et al. The Role of Data Analysis in the Development of Intelligent Energy Networks. IEEE Network. 2017; 31(5): 88-95. doi: 10.1109/mnet.2017.1600319
86. Salehi H, Das S, Biswas S, et al. Data mining methodology employing artificial intelligence and a probabilistic approach for energy-efficient structural health monitoring with noisy and delayed signals. Expert Systems with Applications. 2019; 135: 259-272. doi: 10.1016/j.eswa.2019.05.051
87. Masterson Creber RM, Hickey KT, Maurer MS. Gerontechnologies for Older Patients with Heart Failure: What is the Role of Smartphones, Tablets, and Remote Monitoring Devices in Improving Symptom Monitoring and Self-Care Management? Current Cardiovascular Risk Reports. 2016; 10(10). doi: 10.1007/s12170-016-0511-8
88. Choi HS, Yoon S, Kim J, et al. Calibrating Low-Cost Smart Insole Sensors with Recurrent Neural Networks for Accurate Prediction of Center of Pressure. Sensors. 2024; 24(15): 4765. doi: 10.3390/s24154765
89. Farago E, Chan ADC. Motion artifact synthesis for research in biomedical signal quality analysis. Biomedical Signal Processing and Control. 2021; 68: 102611. doi: 10.1016/j.bspc.2021.102611
90. Zhao Y, Yin Y, Gui G. Lightweight Deep Learning Based Intelligent Edge Surveillance Techniques. IEEE Transactions on Cognitive Communications and Networking. 2020; 6(4): 1146-1154. doi: 10.1109/tccn.2020.2999479
91. Hu D, Huang Z, Yin K, et al. Multidimensional heterogeneous data clustering algorithm for power transmission and transformation equipment. Journal of Intelligent & Fuzzy Systems. 2023; 44(4): 5871-5878. doi: 10.3233/jifs-222924
92. Liu X, Yuan J, Zhao H. Efficient and Intelligent Density and Delta-Distance Clustering Algorithm. Arabian Journal for Science and Engineering. 2018; 43(12): 7177-7187. doi: 10.1007/s13369-017-3060-7