

# Research on Data Processing and Pattern Recognition Algorithms of Intelligent Biosensors in Biomedical Testing

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**Abstract:** Intelligent biosensors are increasingly used in biomedical testing, especially in the field of medical testing, showing great potential. This study mainly discusses the data processing and pattern recognition algorithms of intelligent biosensors in medical testing. In the system design, a power spectral density-based analysis method is proposed for human posture recognition and signal processing to optimize data filtering and feature extraction in the signal processing process. By combining pattern recognition and data processing algorithms, the system realizes efficient human posture detection and diagnosis functions. In the process of system simulation, multiple signal processing techniques along with diverse model simulation approaches are employed to guarantee the precision and resilience of the simulation outcomes. The findings from the study indicate that the suggested algorithm offers substantial benefits in enhancing detection precision and real-time efficiency. Detailed analysis of the system architecture and simulation outputs further corroborates the effectiveness and practicality of the algorithm.

**Keywords:** Intelligent Biosensor; Medical Testing; Human Posture Recognition; Signal Processing; Power Spectral Density.

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## 1. Introduction

With the rapid development of intelligent technology and biomedicine, the application of intelligent biosensors in biomedical testing has gradually attracted widespread attention. Smart biosensors can achieve real-time detection and data analysis of biological signals by integrating a variety of advanced sensing technologies, especially in human posture recognition, disease diagnosis and other aspects, showing great potential [1]. In medical detection, accurate data processing and pattern recognition algorithms are the key links to improve detection accuracy, while signal processing and power spectral density analysis, as basic methods, play an important role in algorithm optimization.

Reference [2] proposed a biological detection system based on multi-sensor fusion, which solved the shortcomings of traditional single sensors in data accuracy and robustness by comprehensive processing of multi-dimensional data. Reference [3] further adopted the power spectral density analysis method to improve the accuracy and efficiency of signal processing, providing more reliable algorithm support for medical detection in complex environments. In addition, reference [4] solved the problem that traditional methods are susceptible to noise interference in dynamic environments by improving the human posture recognition algorithm, and achieved high-precision detection of human posture. These research results provide an important theoretical basis for the data processing and pattern recognition algorithms of smart biosensors discussed in this paper.

The wide application of smart biosensors is not only reflected in signal acquisition and processing, but also includes data processing needs in various biomedical scenarios. Reference [5] proposed a real-time data analysis method based on intelligent sensors, which solved the problem of data processing lag in traditional medical detection and realized dynamic monitoring and analysis of human physiological parameters. At the same time, reference [6] verified the effectiveness of signal processing technology

based on power spectrum density in medical detection through system simulation, which provided a practical basis for the research of this paper.

This article primarily examines the utilization of intelligent biosensors in medical detection, concentrating on their data handling and pattern recognition techniques for human posture analysis and signal processing. In particular, this study aims to refine the signal processing procedure via power spectral density evaluation, integrating pattern recognition methods to enhance the precision of human posture identification. Moreover, the paper will validate the efficiency and stability of the proposed approach through system simulations, performing detailed data analysis to further investigate the algorithm's adaptability and practicality within intricate medical settings.

## 2. Design of Intelligent Biosensor Data Processing and Pattern Recognition System

### 2.1. System Architecture

The intelligent biosensor data processing and pattern recognition system consists of three main modules: data acquisition module, signal processing and analysis module, and pattern recognition and feedback module. The system architecture is shown in Figure 1 (picture cited from Journal of Big Data, 2019, 6(1): 104).

The data acquisition module is responsible for collecting raw data from biosensors, such as electrocardiogram (ECG), electromyography (EMG) and other physiological parameters. Sensors are placed in different parts of the human body and transmit data to the central processing unit through wireless transmission. The data acquisition module must not only have high accuracy, but also ensure low latency and high reliability during data transmission.

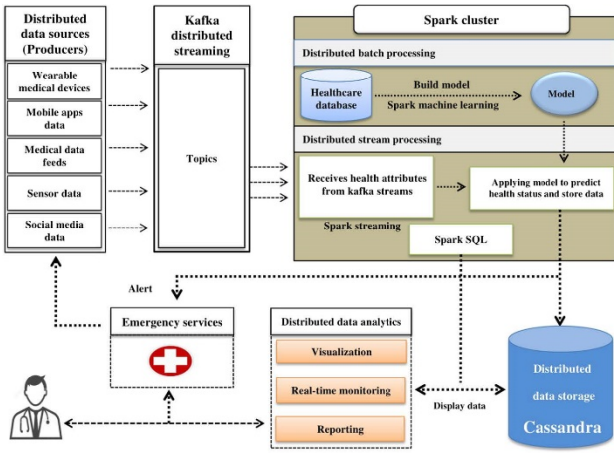


Fig 1. System architecture

The signal processing and analysis module is the core of the system, including data preprocessing, filtering, feature extraction and power spectral density (PSD) analysis. Signal preprocessing includes denoising and baseline correction to ensure data accuracy. Subsequently, the system calculates the frequency domain characteristics of the signal through power spectral density analysis to extract key information [7]. These features include signal energy, frequency distribution, etc., which can be used for subsequent pattern recognition. The effect of signal processing directly affects the accuracy of pattern recognition, so the algorithm design of this module is particularly important.

The pattern recognition and feedback component categorizes and evaluates the input information utilizing the human posture recognition method while integrating earlier signal processing outcomes. More precisely, this component employs machine learning techniques, such as support vector machines (SVM) and convolutional neural networks (CNN), to conduct pattern classification on various physiological data and produce health evaluation reports. Ultimately, the system delivers the analysis outcomes back to the user, offering real-time health recommendations.

## 2.2. System Functions

The functional components of the intelligent biosensor data processing and pattern recognition system include the following: The sensor data module handles the synchronized

collection of multi-channel data to maintain temporal alignment across various physiological signals. Additionally, this component incorporates sensor calibration and signal sampling rate adjustments to cater to the requirements of diverse detection environments. The signal processing function includes sub-modules such as data filtering, noise suppression and signal enhancement. The main task of the signal processing module is to eliminate artifacts and noise in the data to extract features with more diagnostic value. Through power spectral density analysis, the module can identify the main frequency components of the signal, thereby providing a basis for subsequent pattern recognition [8]. The human posture recognition function uses multi-sensor fusion technology combined with deep learning algorithms to perform posture recognition on the collected physiological signals. Through real-time monitoring of posture changes, the module can identify abnormal postures and help doctors or users adjust exercise or treatment plans in a timely manner. Feedback functions include visual interface, voice prompts and intelligent suggestions. The system will feedback the recognition results and health assessment information to the user in the form of charts or texts, and provide personalized health guidance.

## 2.3. System Flow

Figure 2 shows the workflow of the system. The data acquisition module first obtains raw data from multiple biosensors, and enters the signal processing module after preprocessing. The signal processing module filters, denoises and performs frequency domain analysis on the data, and extracts eigenvalues. Subsequently, the pattern recognition module uses these features to perform posture analysis and classification judgment, and finally presents the analysis results to the user through the feedback module. The core of the system lies in the efficiency of its signal processing and pattern recognition [9]. Through power spectral density analysis, the system can accurately identify the physiological signal characteristics under different postures, and accurately classify and evaluate them based on these characteristics. Moreover, when handling data in intricate settings, the system is capable of adaptively fine-tuning the filtering parameters and feature extraction techniques to maintain the completeness and dependability of the signal.

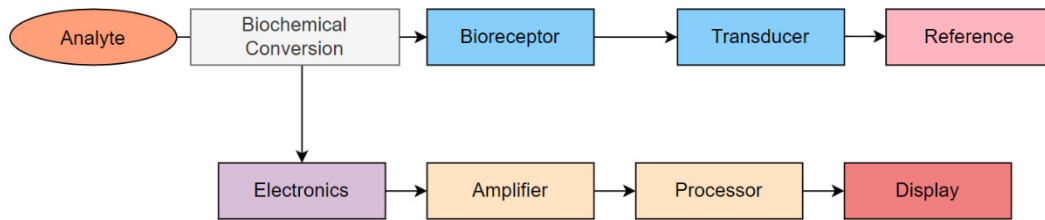


Fig 2. System flow

## 3. Processing and Identification of Human Motion Information

### 3.1. Signal Processing Algorithm

Since the main research is on the motion characteristics of the human body, the Chebyshev two-high-pass filtering method is used to eliminate the influence caused by the second type of factors. The comparison between the filtered signal and the original signal is shown in Figure 3.

This method extracts the seismic waves and time domain

information of each excitation source and plots them into a graph. Some period changes can be seen in Figure 4. In the research of this topic, the spectrum distribution in the frequency domain can be used to discover the characteristics of the data.

In the process of estimating the acceleration power spectrum density, acceleration  $\beta_T(\tau)$  is an acceleration over a certain period of time, and it is Fourier transformed:

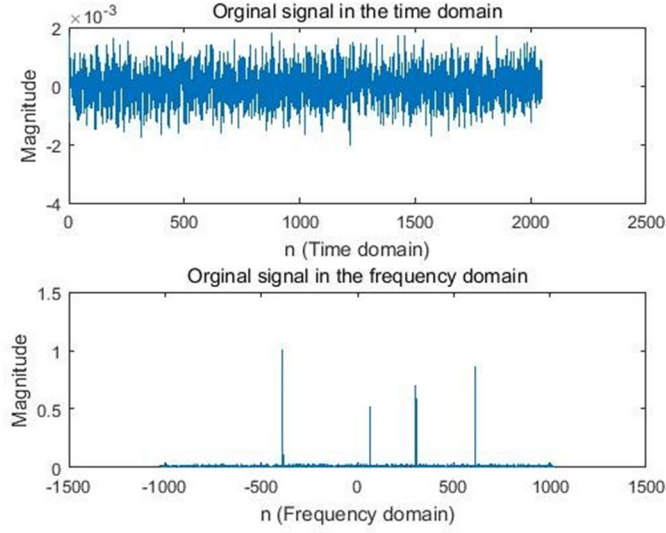


Fig 3. Original signal and filtered signal

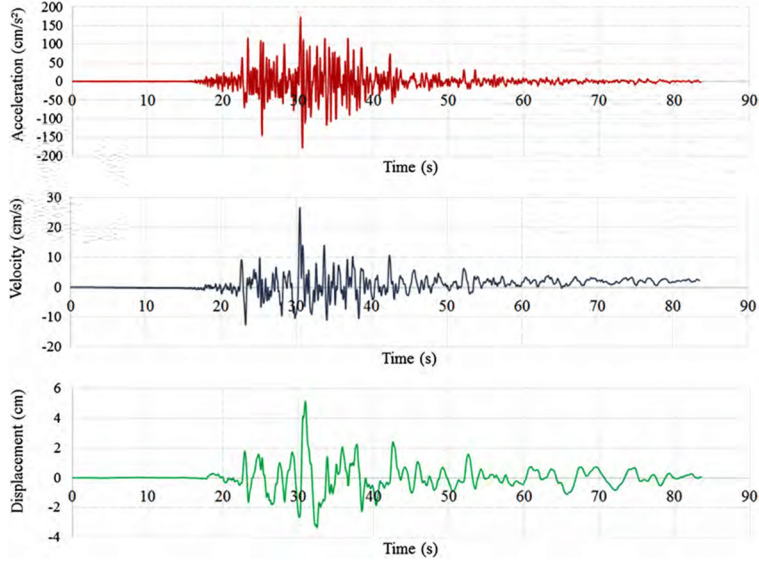


Fig 4. Acceleration and time relationship of a single activity

$$\beta_T(u) = \int_{-\infty}^{\infty} \beta_T(\tau) e^{-i2\pi u\tau} dt = \int_{-T}^T \beta(\tau) e^{-i2\pi u\tau} dt \quad (1)$$

The Batsheva formula is also satisfied:

$$\int_{-\infty}^{\infty} \beta_T^2(\tau) dt = \int_{-\infty}^{\infty} |\beta_T(u)|^2 du \quad (2)$$

The left-hand side of the equation denotes all accelerations within the time domain, while the integral on the right-hand side is referred to as the energy spectral density, representing the energy distributed across each frequency. The energy spectral density is a non-negative real value.

Separating equation  $\beta_T(u) = \begin{cases} \beta(t) & |\tau| \leq T \\ 0 & |\tau| > T \end{cases}$  from

the other side and allowing  $T$  to go to infinity yields:

$$\lim_{T \rightarrow \infty} \frac{1}{2T} \int_{-T}^T \beta^2(\tau) d\tau = \int_{-\infty}^{\infty} \lim_{T \rightarrow \infty} \frac{1}{2T} |\beta_T(u)|^2 du \quad (3)$$

From formula (3), it can be seen that the density of the power spectrum is:

$$\rho(u) = \lim_{T \rightarrow \infty} \frac{1}{2T} |\beta_T(u)|^2 \quad (4)$$

Then, a comparison curve of the dynamic spectrum

distribution under the action of walking load and main building load is given. As can be seen from Figure 5, under different effective accelerations, the peaks and their corresponding coordinates are different. Finally, the image is statistically analyzed using time domain, frequency domain and multiple histograms to obtain 60 feature points.

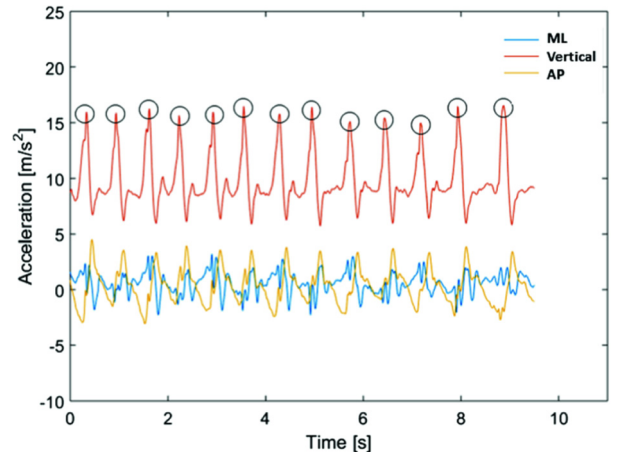


Fig 5. Comparison of acceleration power spectrum density of walking and going upstairs

### 3.2. Human Posture Recognition

This project intends to use the above method to identify six behaviors of human walking, going up and down stairs, sitting and lying, and use a combination of recurrent neural network and LSTM to identify six behaviors of human walking, going up and down stairs, sitting and lying, etc. After testing multiple optimization methods, the Adam optimization method was finally selected to optimize the parameters of the system [10]. The image classification effect was obtained through 9 layers of recurrent LSTM, 1 fully connected layer, and an output layer. The model can obtain a prediction accuracy of 92.1%.

### 4. Experiment and Comparative Analysis

The practicality of the proposed approach was validated through experimental testing. A Lenovo Y9000K2019SE laptop served as the primary device for this experiment [11]. The public HAR dataset was examined using the aforementioned method, with human activities identified via Matlab’s neural network software. Ultimately, the training, validation, and test sets, along with the overall confusion matrix, were obtained. The receiver operating characteristic for the neural network is depicted by the ROC curve (Figure 6).

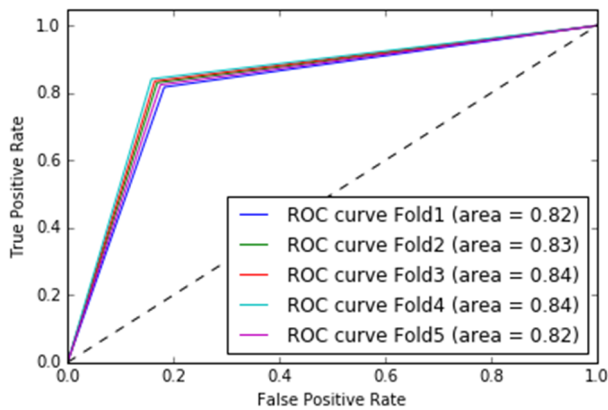


Fig 6. ROC curve

In the same experimental environment, the public HAR database is used to analyze human behaviors in 6 different postures to verify the effectiveness of the proposed method. The experimental data is compared with the human behavior recognition method given (Table 1).

Table 1. Comparison of recognition accuracy and training time of the algorithm in this paper and other algorithm models

Model name	Recognition accuracy/%	Training time/s
CNN	90.29	13.39
J48	84.25	9.59
Multilayer perceptron	90.78	10.15
SVM	90.98	7.16
Algorithm in this paper	91.18	5.22

Under the same experimental conditions, the method described in this paper is not much different from other methods, but its operation speed is greatly accelerated, which is very beneficial for rapid data learning.

### 5. Conclusion

This research emphasizes the utilization of intelligent biosensors in biomedical examinations and introduces an effective data handling and pattern recognition algorithm. For addressing the challenge of human posture detection in medical testing, power spectral density analysis is employed to optimize signal processing. In system simulations, the applicability and robustness of the proposed approach across various detection scenarios are validated by designing and integrating multiple algorithms. The findings indicate that the smart biosensor combined with power spectral density-based signal processing technology significantly enhances the accuracy of human posture identification while maintaining strong stability in noisy environments. In the simulations, the algorithm demonstrates excellent real-time performance and precision, meeting stringent data processing requirements in medical testing. Detailed data analysis further confirms the effectiveness of the model simulation. In conclusion, this research offers an innovative and practical solution in the medical testing field, playing a key role in advancing the application and development of intelligent biosensors.

### References

- [1] Mudhulu, S., Channegowda, M., Balaji, S., Khosla, A., Sekhar, P. Trends in graphene-based E-skin and artificial intelligence for biomedical applications—a review. *IEEE Sensors Journal*, vol. 23, pp. 18963-18976, August 2023.
- [2] Sagdic, K., Eş, I., Sitti, M., Inci, F. Smart materials: rational design in biosystems via artificial intelligence. *Trends in Biotechnology*, vol. 40, pp. 987-1003, August 2022.
- [3] Sonawani, S., Patil, K., Natarajan, P. Biomedical signal processing for health monitoring applications: a review. *International Journal of Applied Systemic Studies*, vol. 10, pp. 44-69, March 2023.
- [4] Athanasopoulou, K., Daneva, G.N., Adamopoulos, P.G., Scorilas, A. Artificial intelligence: the milestone in modern biomedical research. *BioMedInformatics*, vol. 2, pp. 727-744, December 2022.
- [5] Kaushik, A.K., Dhau, J.S., Gohel, H., Mishra, Y.K., Kateb, B., Kim, N.Y., Goswami, D.Y. Electrochemical SARS-CoV-2 sensing at point-of-care and artificial intelligence for intelligent COVID-19 management. *ACS Applied Bio Materials*, vol. 3, pp. 7306-7325, November 2020.
- [6] Haick, H., Tang, N. Artificial intelligence in medical sensors for clinical decisions. *ACS Nano*, vol. 15, pp. 3557-3567, March 2021.
- [7] Kasture, K., Shende, P. Amalgamation of artificial intelligence with nanoscience for biomedical applications. *Archives of Computational Methods in Engineering*, vol. 30, pp. 4667-4685, August 2023.
- [8] Ramalingam, M., Jaisankar, A., Cheng, L., Krishnan, S., Lan, L., Hassan, A., Marrazza, G. Impact of nanotechnology on conventional and artificial intelligence-based biosensing strategies for the detection of viruses. *Discover Nano*, vol. 18, pp. 58-78, June 2023.
- [9] Amethiya, Y., Pipariya, P., Patel, S., Shah, M. Comparative analysis of breast cancer detection using machine learning and biosensors. *Intelligent Medicine*, vol. 2, pp. 69-81, May 2022.
- [10] McRae, M.P., Rajsri, K.S., Alcorn, T.M., McDevitt, J.T. Smart diagnostics: combining artificial intelligence and in vitro diagnostics. *Sensors*, vol. 22, pp. 6355-6372, September 2022.
- [11] Chugh, V., Basu, A., Kaushik, A., Bhansali, S., Basu, A.K. Employing nano-enabled artificial intelligence (AI)-based smart technologies for prediction, screening, and detection of cancer. *Nanoscale*, vol. 16, pp. 5458-5486, March 2024.