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IoT-enabled real-time health monitoring system for adolescent physical rehabilitation

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This study aims to develop an intelligent system leveraging Internet of Thing (IoT) technology to enhance the precision of youth physical training monitoring and improve training outcomes. A wearable device incorporating Micro Electro Mechanical Systems (MEMS) sensors is integrated to collect real-time motion data. Advanced signal processing and filtering techniques are employed to minimize noise interference and improve data accuracy. A particle swarm optimization support vector machine (PSO-SVM) algorithm is utilized to classify motion patterns. To evaluate the system's performance, experiments were conducted to assess motion pattern recognition accuracy, response time, real-time analysis capabilities, and system stability and capacity. The methods we use and the data we collect are from public datasets, do not involve privacy protection for adolescents, and have been approved by the institutional ethics committee. The system demonstrated a motion pattern recognition accuracy exceeding 95% and a response time consistently below 250 ms under various network conditions. Practical applications revealed the system's effectiveness in health monitoring, leading to improved physical fitness and positive rehabilitation outcomes for adolescent patients. This study offers an innovative digital solution for adolescent physical training and health monitoring. The system's strong application potential and valuable insights contribute to the advancement of related research.

Keywords Physical training, Internet of thing, Artificial intelligence, Machine learning, Health monitoring

Physical training has received significant attention in recent years, especially in healthcare and wellness contexts[1]. This trend highlights the growing importance of adolescent physical fitness in healthcare[2]. Physical fitness is the body's ability to efficiently perform tasks and skillfully navigate environmental challenges through muscular engagement. It is a cornerstone of overall well-being[3].

Physical training is not merely an exercise regimen but a vital strategy to fortify the body's adaptive mechanisms against external stresses[4]. The importance of such training is further amplified in healthcare, where it serves as a preventative measure against various ailments, including cardiovascular diseases and mental health disorders[5]. Consequently, physical training emerges as a regime designed to condition the body for enhanced adaptability to external environments.

Adolescents in school settings face challenges such as academic stress, limited access to high-quality physical training, and rising health issues like myopia, obesity, and muscle weakness[6]. IoT-based intelligent systems can bridge these gaps by providing actionable insights, real-time feedback, and adaptive training protocols[7,8]. For instance, wearable devices can monitor heart rate, motion patterns, and activity levels, ensuring that training regimens are both effective and safe.

The discourse surrounding physical fitness training has increasingly intersected with healthcare due to the growing integration of IoT-based solutions in monitoring and enhancing health outcomes. In the context of adolescent health, continuous monitoring and data-driven interventions are critical[9]. Therefore, this study explores the development of an IoT-integrated intelligent system for adolescent health monitoring and physical training. The proposed system leverages advanced machine learning models (e.g., PSO-SVM) for motion recognition, aiming to enhance physical fitness, address individual health needs, and prevent injuries.

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Functional training	Non-functional training
Integrated action	Isolated action
Flexible	Inflexible
Exists in real life	Does not exist in real life
Satisfies physical characteristics	Does not satisfy physical characteristics
Satisfies biomechanical characteristics	Does not satisfy biomechanical characteristics
Dependent on proprioception	Human adaptation
Motor chain	Non-motor chain

Table 1. Differences between functional and non-functional training.

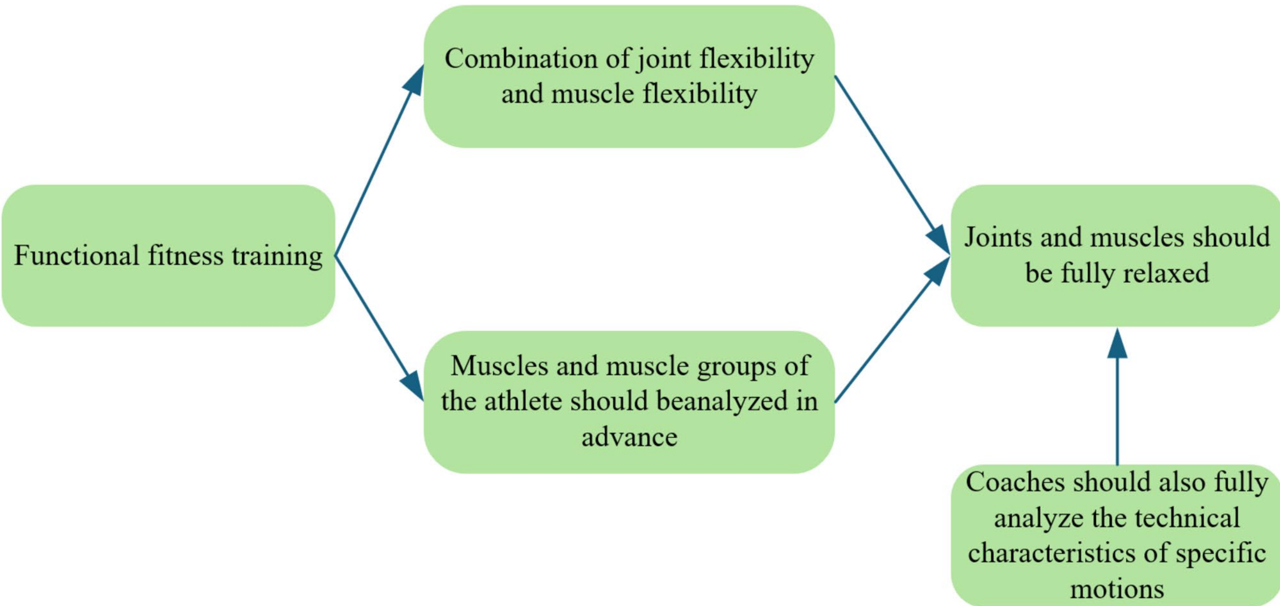

Fig. 1. Functional fitness training process.

Overview of youth physical training

Functional training

The contemporary paradigm in physical training content has shifted from a focus on strength and endurance training to an emphasis on functional training targeting neuromotor systems[10]. Functional training, rooted in medical rehabilitation[11], involves therapists guiding patients through exercises that simulate daily movements. This approach accelerates their return to normal life. Functional training focuses on movement patterns, optimizing fundamental athletic abilities through posture and sequence training[12]. Through systematic training in movement patterns, spinal strength, power chains, recovery, speed, explosive power, and energy systems, a continuous improvement framework for specific athletic skills can be established. Functional training, thus, focuses primarily on enhancing movement patterns, operating under the principles of pre-training assessment, prioritizing stability over motion, and emphasizing injury prevention over physical ability enhancement[13].

Several key characteristics distinguish functional training. Primarily, it aligns the exercise method with the target movement, ensuring a direct correlation between training and functional application. Functional training emphasizes holistic movement by integrating core body interactions, proprioception, and neurological control. Table 1 elucidates the distinctions between functional and non-functional training, providing a comparative analysis of their respective methodologies and outcomes. This approach underscores the holistic nature of functional training, where exercises are not only about physical exertion but also about enhancing the body's natural movement patterns and neurological connections for improved overall performance and injury prevention.

Functional fitness training combines joint and muscle flexibility. Additionally, pre-training analysis of muscle groups helps determine whether distal or proximal fixation is needed, guiding the selection of supplementary tools. What is more, after training, the joints and muscles should be fully relaxed to facilitate the improvement of joint flexibility and muscle elasticity. In summary, the functional fitness training process is shown in Fig. 1.

Sports characteristics of youth

Physical fitness training necessitates tailored content and methodologies to cater to the distinctive physical and psychological attributes of diverse demographic groups[14,15]. Employing customized training approaches that align with the unique characteristics of each group not only facilitates adaptation to the exercises but also maximizes their efficacy. In the context of adolescents, it is pertinent to note that their physical functions are in a state of maturation, and their athletic capabilities are generally on an upward trajectory. A notable physiological aspect of adolescence is the heightened rigidity and elasticity of bones, which are less calcified compared to those in adults[16]. This period is also marked by rapid growth in stature, often accompanied by an imbalance in muscle development.

The respiratory system in adolescents is approaching full maturity, characterized by high metabolic rates. However, their lung capacity typically ranges from low to moderate, with corresponding limitations in aerobic endurance. Consequently, physical training programs for adolescents should judiciously increase both aerobic and anaerobic capacities[17]. This approach should integrate anaerobic, aerobic, and interval training modalities to effectively stimulate and enhance the respiratory system, particularly pertinent for secondary school students[18]. Concurrently, the neurological development of adolescents is nearing maturity, with motor neuromuscular coordination remaining at a relatively high level. Therefore, incorporating motor nerve exercises into their training regimen can significantly improve their reactive abilities and coordination, crucial elements for their overall physical development and athletic performance.

Motion chain theory

The motion chain is a scientific model that explores the interactions, changes in physical and chemical characteristics, and functional transformations of the skeleton, joints, and muscles of the human body[19]. The study of the human kinetic chain is a key step to ensure the motility and correlation of the entire motor system. In other words, the structure of the human kinetic chain determines the function of functional movements, and the theory of the human kinetic chain is one of the theoretical sources for designing functional training[20]. The role of the neural chain can be broadly reflected in the sensorimotor system and the neurodevelopmental motor patterns[21]. The sensorimotor system could be divided into two main forms, the protective reflex stabilization chain and the sensorimotor chain. The protective reflex is a skin-muscle reflex that is generated by stimulating the skin or mucous membranes. The sensorimotor chain consists of the reflex stabilization chain and the sensorimotor adaptation chain.

In fact, all functions of the human body are based on the completion of movements. To be specific, movement is a process governed by the nervous system, and is conducted in a balanced manner by a series of muscles, fascia, tendons, bones, joints and other systems[22]. Functional movement is the ability to provide and maintain flexibility, coordination, and stability of the muscles in the movement chain while accurately and effectively integrating the basic movement patterns of the body[23]. Figure 2 illustrates the different combinations of functional movements of human movement.

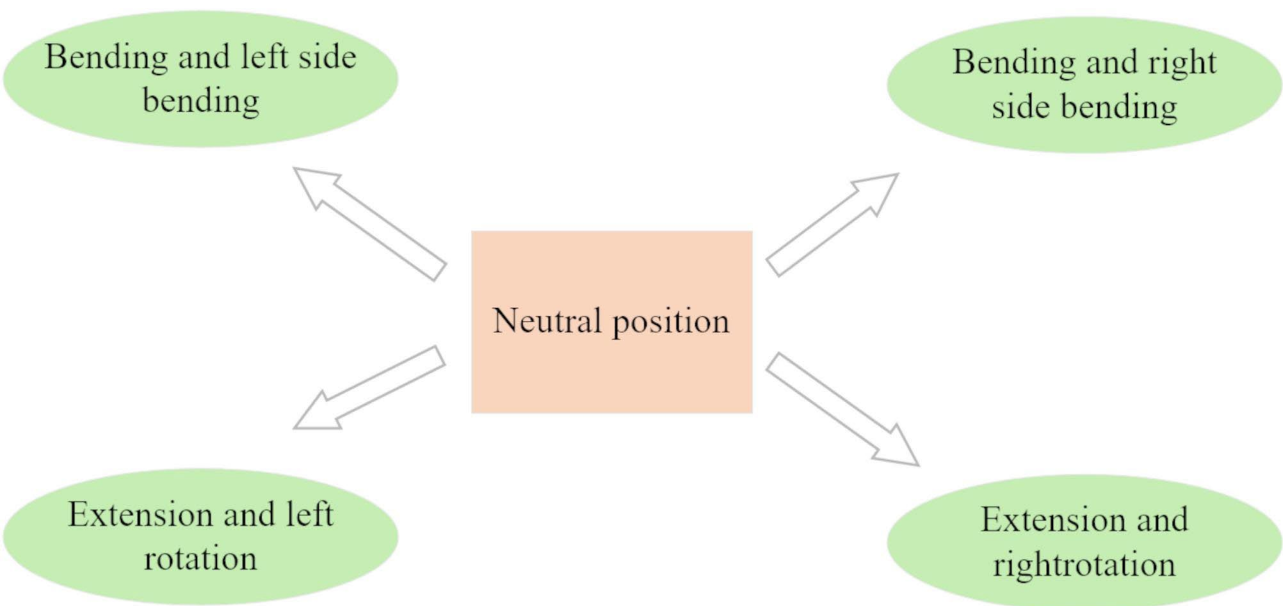

Fig. 2. Combinations of functional movements in human motio.

Construction of intelligent system for physical training

Deployment and selection of sensor nodes

The design of the minimum hardware system designed in this paper mainly contains sensor module, microprocessor module, power supply module communication link. The overall framework of the system is shown in Fig. 3.

The information sensing unit of this design is MEMS sensor. The selection of waist and thigh locations for MEMS sensor deployment is grounded in the biomechanical principles of the Hanavan human body model[24].

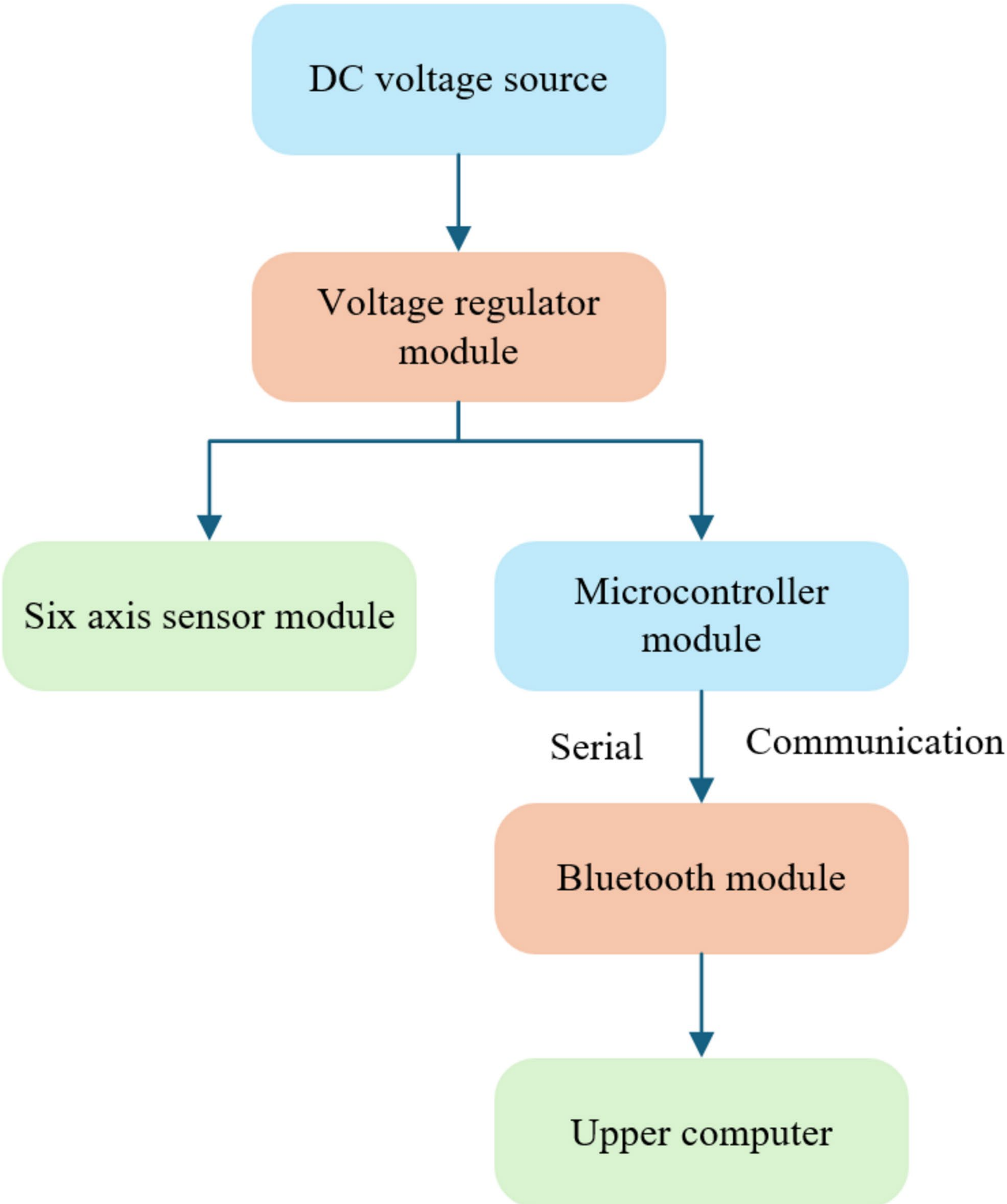

Fig. 3. Block diagram of the proposed human motion pattern detection system.

The Hanavan model provides a framework for understanding the distribution of body segments and their contributions to overall motion dynamics. The waist, near the body's center of gravity, captures global motion trends such as posture shifts and rotational movements, which are essential for understanding the overall activity pattern. The thighs, being large and stable segments, provide critical information on lower limb kinematics, including stride length, acceleration, and joint angles. These locations are optimal for capturing the most informative motion data while minimizing noise from high-frequency movements of distal segments like the ankles and wrists. Considering the application scenario of this model, the system design needs to fulfill the requirements of high accuracy, small size, low power consumption and easy wearability. In order to design a pattern recognition system with the highest accuracy using the minimum number of sensor units, we need to find the optimal placement nodes. The Inertial Measuring Unit (IMU) is used to measure the angular velocity and linear acceleration of the lower limb segments as direct biomechanical variables. At the same time, the direct output of the IMU is used to indirectly calculate the lower limb joint and segment inclination in the sagittal plane. The output undergoes several signal conditioning stages to remove noise and bias. In addition, the effect of misalignment on the raw data was eliminated by propriety calibration of the sensors. Therefore, the following conclusion was drawn: the optimal locations for the expression of human movement patterns are the waist and the thighs. The deployment location of the sensor nodes is thus determined.

Variations in adolescent anthropometrics, such as height, weight, and body proportions, can significantly impact sensor calibration and data consistency. Taller adolescents may have different segment lengths and moment arms, affecting the interpretation of angular velocity and acceleration data. Heavier individuals may introduce more soft tissue movement, leading to potential sensor displacement and increased noise in the raw signals. To address these challenges, the system employs a calibration routine that accounts for individual differences. The IMU system error calibration process, described in Sect. 3.2, is designed to correct for scale factor and zero-bias errors specific to each sensor and user. Additionally, the feature extraction process of empirical mode decomposition (EEMD) used in this study is robust to small changes in signal morphology, ensuring consistent pattern recognition among different populations.

IMU system error calibration

In an ideal inertial guidance coordinate system, the three-axis accelerometer coordinate system $(\lambda_i, \lambda_j, \lambda_k)$ and the three-axis gyroscope coordinate system (ξ_i, ξ_j, ξ_k) are perfectly coincident. Due to the presence of design and machining errors, an error angle will exist between the two. There will also be a scale factor and zero-bias error, which are the main factors affecting the accuracy of the coordinate results. In this study, the algorithm of multi-target capturing positioning information is used to collect the acceleration values of the three axes, i.e., λ_i λ_j, λ_k, under various static conditions, which are used as the solution conditions for the model parameters of the accelerometer; and then the calibrated data are used to assist in calibrating the angular parameters and optimizing the system's reference coordinate system.

Data preprocessing

Outlier detection

The front-end data of this system is acquired through IMU sensors. When the components are guaranteed to work under the rated electrical state, data anomalies generally do not occur. However, considering the application scenarios of wearable devices, there is a possibility that the sensor data acquisition process may result in phenomena such as device dropping, power supply dropout, excessive environmental noise, etc., at which time the system front-end data will have abnormal values. Abstractly speaking, outliers are patterns that deviate from the expected normal behavior. Then, the normal behavior pattern can be represented by a region, and all normal observations can be regarded as belonging to this normal region, and those that do not belong to this region are regarded as outliers. There are various outlier detection methods, such as distance-based, probability distribution-based, and base-based. Here we are using the probability distribution-based method, which utilizes the most common normal distribution in statistics. According to the distribution probability situation of the data acquired by the sensor, we can determine whether the value is abnormal or not.

Let the data sample points be $(i_1, i_2, i_3, \cdots, i_t)$, the mean value μ and variance σ can be calculated by Eq. (1) and Eq. (2).

$$\mu = \frac{1}{t}\sum{}_{x=1}^{t} i_x \tag{1}$$

$$\sigma^2 = \frac{1}{t}\sum{}_{x=1}^{t} (i_x - \mu)^2 \tag{2}$$

If the data samples fall in the above interval, the data is determined to be normal, if the data samples are not in this interval, the data is determined to be an outlier, and directly discarded for processing. Comprehensive analysis of the above, the outlier processing flow used in this paper is shown in Fig. 4.

Data noise reduction

For the collected data, in addition to outlier detection and elimination, it is also necessary to perform noise reduction and filtering on the data. Because the data transmission process may be subject to mechanical noise, electronic noise and electromagnetic wave signal interference, so noise reduction filtering is a necessary processing step before obtaining useful data. Here, we use op-amp MAX9203 hysteresis comparator to realize the data noise reduction. The supply voltage of the op-amp is ± 5 V, and the circuit parameters are designed by combining the general frequency bandwidth of human motion information. The built circuit is shown in Fig. 5.

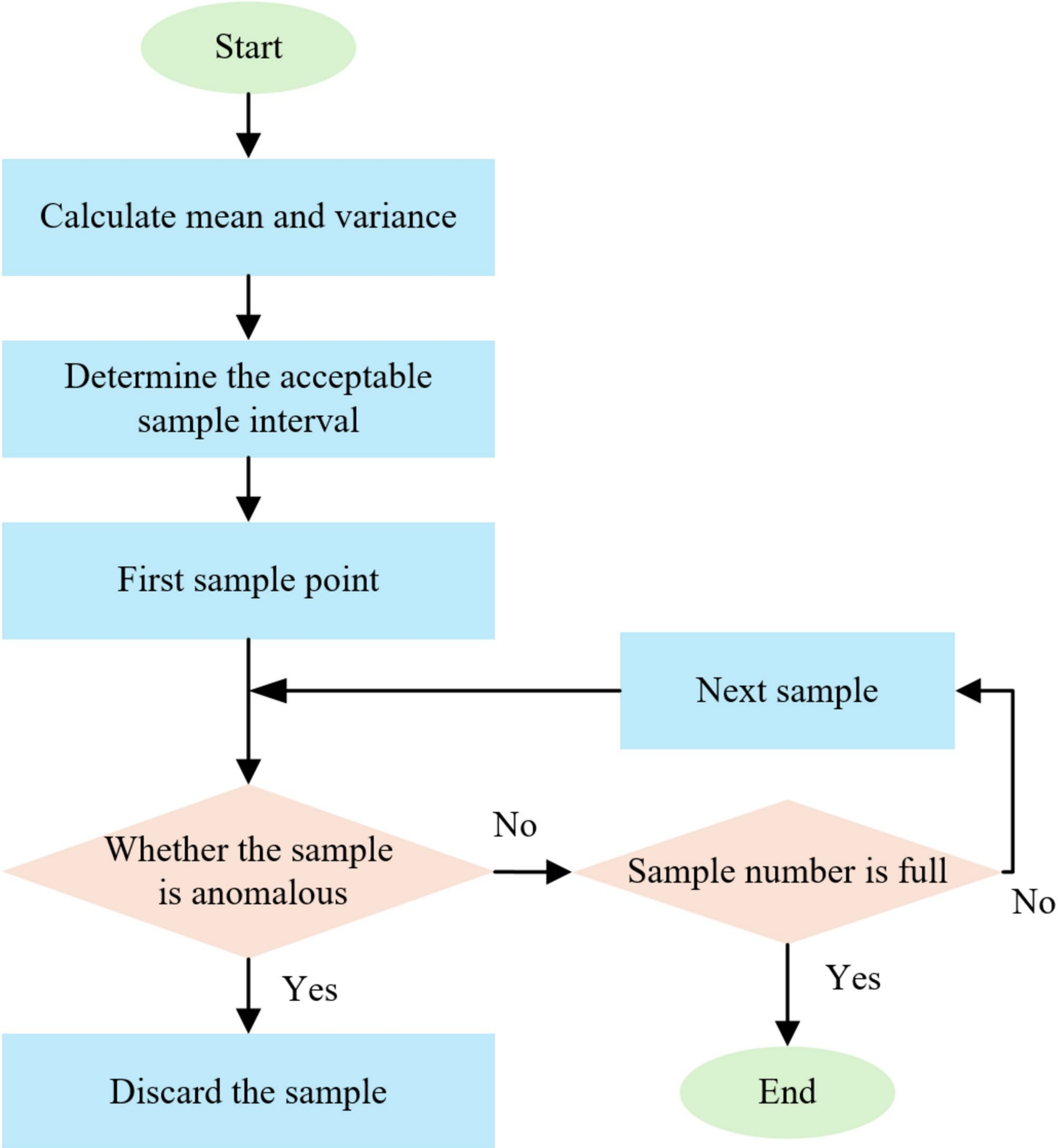

Fig. 4. Anomaly handling process.

The hysteresis comparator circuit employed in this study for noise reduction offers distinct advantages in the context of real-time motion data processing. Unlike software-based methods such as wavelet transforms and Kalman filters, the hysteresis comparator operates at the hardware level, providing immediate noise attenuation without introducing additional computational latency. This is particularly critical in real-time health monitoring applications where timely feedback is essential for effective intervention.

Wavelet transforms are powerful for decomposing signals into different frequency bands and removing noise through thresholding, but they require significant computational resources and are typically implemented offline or on powerful processors. Kalman filters, while effective for dynamic systems, demand precise modeling of the system dynamics and measurement noise characteristics, which can be challenging in the unpredictable environments of physical rehabilitation.

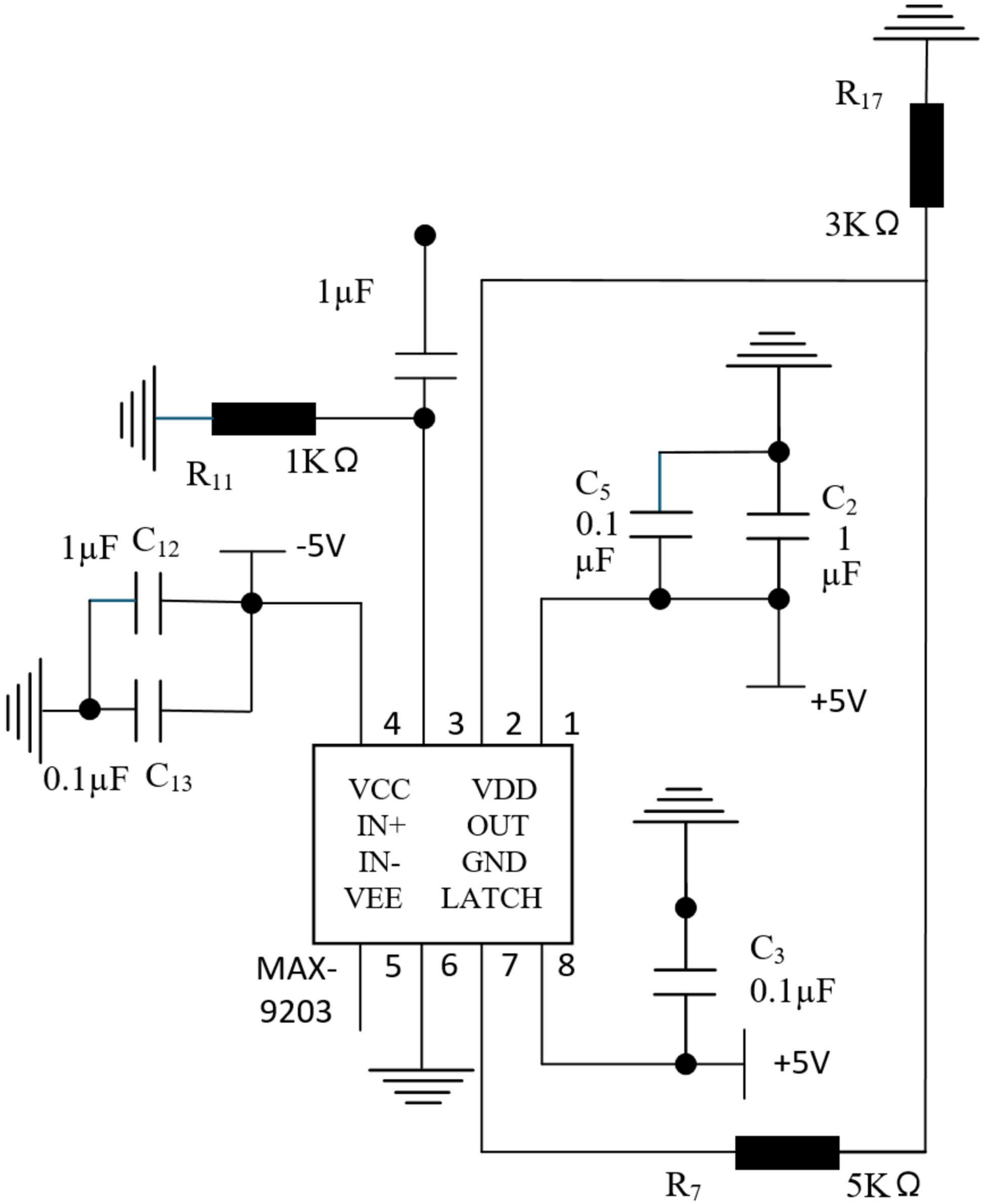

Fig. 5. Hysteresis comparator circuit for noise reduction in motion data.

The hardware-based approach adopted in this system ensures minimal latency, as the noise reduction is accomplished directly within the analog domain before digitization. This contrasts with algorithmic methods that must process digitized signals, introducing delays due to sampling, quantization, and computational processing. However, hardware solutions like the hysteresis comparator may lack the adaptability of software-based methods in handling diverse noise profiles.

The choice between hardware and algorithmic noise reduction involves trade-offs in latency, computational resource consumption, and flexibility. Hardware-based methods, such as the hysteresis comparator, excel in low-latency applications and consume fewer computational resources, making them ideal for wearable devices with limited processing power. They are less susceptible to variations in software performance and can operate independently of the system's main processor.

On the other hand, algorithmic approaches offer greater flexibility in adapting to different noise environments and signal characteristics. They can be updated and optimized post-deployment through software revisions, whereas hardware circuits require physical redesigns for modifications.

In this study, the hysteresis comparator circuit was chosen for its balance of effectiveness, simplicity, and compatibility with the system's real-time requirements.

Improved SVM based human motion pattern recognition

PSO-SVM algorithm

Traditional Support Vector Machines (SVMs) are widely used for pattern recognition tasks due to their excellent classification performance, but their performance depends heavily on the choice of parameters. The particle swarm optimization (PSO) algorithm, as an effective global optimization algorithm, can be used to optimize the parameters of SVM. In this paper, a PSO algorithm is proposed to optimize the SVM model for human motion pattern recognition. PSO-SVM was selected over other classification models (e.g., Random Forest) due to its dual advantages in handling high-dimensional motion data and optimizing hyperparameters efficiently. Unlike traditional SVM models that require meticulous parameter tuning, our PSO-SVM algorithm optimizes the penalty parameter *C* and kernel parameter *a* through particle swarm optimization, enhancing classification accuracy and reducing overfitting risks.

Support vector machine is a machine learning method that follows the principle of minimizing structural risk while reducing the error and learning complexity of the training set. The basic idea is to determine a hyperplane and use that hyperplane to distinguish the information data as correctly as possible. Thus, the classification problem is transformed into a quadratic programming problem, namely

$$\left\{ \begin{array}{l} \max \sum_{x=1}^{t} \alpha_x - \frac{1}{2} \sum_{x=1}^{t} \sum_{y=1}^{t} j_x j_y \alpha_x \alpha_y Z\left(i_x, i_y\right) \\ s.n. \left\{ \begin{array}{c} \sum_{x=1}^{t} j_x \alpha_x = 0 \\ 0 \leqslant \alpha_x \leqslant C,\ x = 1, 2, \cdots, t \end{array} \right. \end{array} \right. \tag{3}$$

where i_x is the training sample input variable; j_y is the corresponding output variable; α_x, α_y are the Lagrange multipliers; *C* is the penalty parameter; $Z\left(i_x, i_y\right)$ is the kernel function. The motion recognition problem is actually a multi-input, single-output nonlinear mapping problem, which requires the use of radial basis function (RBF) as the kernel function of SVM, i.e.:

$$Z\left(i_x, i_y\right) = \exp\left(-a\|i_x - i_y\|^2\right) a > 0 \tag{4}$$

Where: *a* is the kernel parameter.

The final classification function of the support vector machine is obtained as:

$$f\left(i\right) = sign\left[\sum_{x=1}^{t} \alpha_x Z\left(i, i_x\right)\right] = sign\left[\sum_{x=1}^{t} \alpha_x \exp\left(-a\|i - i_x\|^2 - h\right)\right] \tag{5}$$

where *h* is the bias. The support vector machine classification performance depends on the selection of the penalty parameter *C* and the kernel parameter *a*. Too small a kernel parameter *a* results in weak performance of the trained model, while too large a kernel parameter a results in overfitting of the training samples. The penalty parameter *C* affects the maximum impermissible error, and both of them affect the performance of the model. Therefore, PSO is used to optimize the parameters *C*, *a* of the SVM model. PSO is an algorithm based on an iterative model, where the value of the function to be optimized (the classification error function) is set as the fitness of each particle throughout the parameter optimization phase. The initial stage is a population of particles, where each particle vector represents an SVM model corresponding to a different *C*, *a* in the model, i.e. a potential optimal solution. Particle characteristics are described in terms of position, velocity and fitness values. The factors affecting the velocity and direction of particle motion are the historical motion information of itself and the population and the historical optimal position. The velocity of a particle is defined as the distance it moves in each iteration. So the velocity of the particle in *d*-dimensional subspace is:

$$Q_{xd}^{z+1} = \delta\, Q_{xd}^{z} + c_1 r_1 \left(U_{xd}^{z} - P_{xd}^{z}\right) + c_2 r_2 \left(U_{ad}^{z} - P_{xd}^{z}\right) \tag{6}$$

$$P_{xd}^{z+1} = P_{xd}^{z} + Q_{xd}^{z+1} \tag{7}$$

where δ is the inertia weight; c_1 and c_2 are the learning factors, which represent the local and global search ability of the particle swarm algorithm. P_{xd}^{z} is the position of particle *x* in the *z*-th iteration in the *d*-th dimension. U_{xd}^{z} is the extreme position of particle *x* in the individual; U_{ad}^{z} is the extreme position of particle *x* in the group.

The PSO parameters were optimized through iterative grid search and cross-validation. The inertia weight (δ) was initialized at 0.9 to prioritize global exploration, then linearly reduced to 0.4 to shift toward local refinement. Learning factors ($c_1 = c_2 = 2.0$) balanced individual and social learning, while swarm size (50 particles) and iterations (100 cycles) were determined via convergence tests. Fitness was defined as classification error minimization, ensuring alignment with the SVM's objective function. This approach achieved stable convergence within 80 iterations, confirming parameter robustness.

Feature extraction

Empirical Mode Decomposition (EMD) is an adaptive analysis method for nonlinear and nonsmooth signals[25]. It can decompose a complex signal into a collection of intrinsic mode functions (IMFs) based on the local characteristic time scale of the signal. However, it cannot accurately reveal signal feature information due to the problem of mode mixing. To alleviate the mode mixing problem that occurs in EMD, ensemble empirical mode decomposition (EEMD) is proposed. Using EEMD, components with real physical meaning can be extracted from the signal.

The main advantages of EEMD over standard EMD are as follows:

(1) Noise-Assisted Analysis: By adding white noise, EEMD introduces variability that helps separate overlapping frequency components. The noise acts as a "probing signal," ensuring that each IMF corresponds to a distinct physical mode.
(2) Improved Robustness: Averaging multiple decompositions (each with different noise realizations) cancels out the added noise while preserving the true signal components. This reduces mode mixing and enhances the interpretability of motion patterns.
(3) Adaptability to Nonlinear Signals: EEMD's noise-assisted approach is particularly effective for adolescent motion data, which often exhibits irregular and transient features due to rapid physiological changes.

In order to extract the EEMD features, a white noise of finite amplitude is added to the signal, and the added white noise will fill the entire time-frequency space uniformly. When signals are added to a uniformly distributed white background, the different signals are automatically projected into the background built by the white noise at an appropriate reference scale. As the number of averaging times increases, the residual noise decreases, which can effectively improve the problem of frequency aliasing that tends to occur in EMD decomposition. Considering the characteristics of the data acquired by inertial sensors, which are generally nonlinear and nonsmooth signals, decomposing the signals and extracting the effective parameters using EEMD is a key step in motion recognition. The feature extraction process is as follows: the waist sensor node is close to the center of gravity of the human body, which is mainly used to detect the overall motion trend of the human body; the thigh area sensors are used to detect the motion details, such as the speed of the motion, the angle of the motion and so on. The six-axis sensors on each node can obtain the acceleration information (λ_i λ_j, λ_k) and angular velocity information (ξ_i, ξ_j, ξ_k) in three axis directions at the same time. For the motion data in the three axes directions, the nodes can measure the inertial signal components in the *i*, *j*, and *k* directions, which are used to express the motion of the human body in different directions. The combined acceleration and combined angular velocity are used to express the overall motion of the limb. The calculation formula is as follows:

$$\lambda = \sqrt{\lambda_i^2 + \lambda_j^2 + \lambda_k^2} \tag{8}$$

$$\xi = \sqrt{\xi_i^2 + \xi_j^2 + \xi_k^2} \tag{9}$$

In our study, we optimized several key parameters to ensure the robustness of the EEMD process without overcomplicating the decomposition:

Noise Amplitude: We used a finite amplitude white noise. The amplitude was set to a level that was sufficient to fill the time-frequency space without overwhelming the original signal components. This was determined through empirical testing to ensure that the noise contributed to the separation of signal features without introducing excessive artifacts.

Ensemble Size: The number of averages (ensemble size) was optimized to balance between the reduction of residual noise and computational efficiency. A larger ensemble size generally leads to better suppression of residual noise but increases computational load. We found that an ensemble size of 100 provided a good compromise, effectively reducing the impact of added noise while keeping the computation time within acceptable limits for real-time processing requirements.

These parameter choices were validated through experimental evaluation, ensuring that the EEMD process reliably extracted meaningful features from the nonlinear motion signals captured by the MEMS sensors.

Hierarchical algorithm

The patterns detected by the model in this paper mainly target the basic physical training patterns in the daily life of adolescents, such as standing, sitting, walking at a constant speed, accelerating running, going up and down the stairs, and so on. In order to further improve the efficiency of extracting features from motion signals, we classify the signals in advance according to their features. Firstly, the signal can be categorized into static and dynamic. Static motion patterns such as sitting, lying, standing; dynamic motion patterns such as walking, running and so on. On this basis, the motion patterns can be obtained more quickly by analyzing the posture of the motion patterns in combination with the angular velocity sensor. The result of motion state classification is shown in Fig. 6.

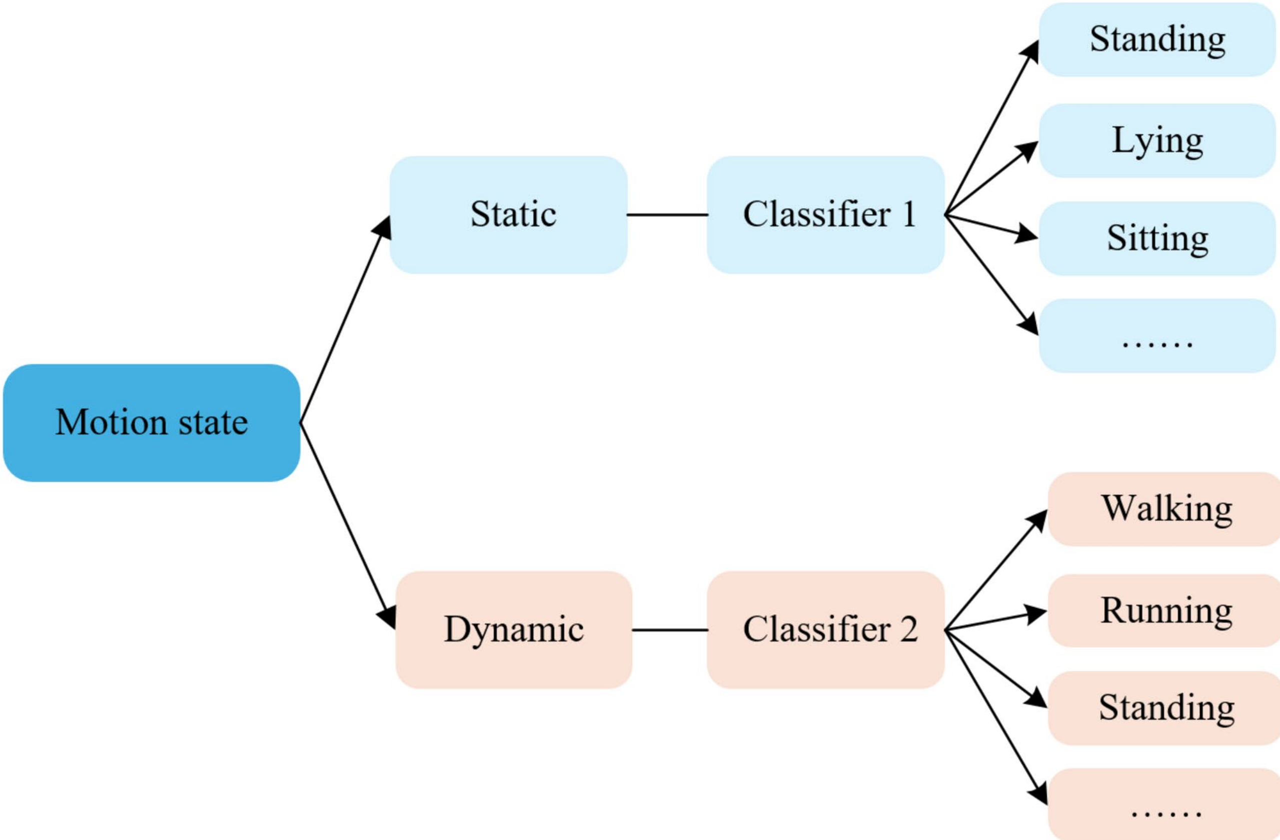

Fig. 6. PSO- SVM classification results.

Motion mode	System classification accuracy (%)	Manual labeling accuracy (%)	Deviation (%)
Walking	97.5	98.0	0.5
Running	95.3	94.8	0.5
Standing	96.7	97.0	0.3
Pushing and pulling	96.1	96.5	0.4

Table 2. Classification accuracy of different motion modes.

System performance testing and analysis
Test environment and experimental setup
The test environment is a simulated youth physical training scenario, using IoT-based wearable sensors to collect real-time motion data, which are transmitted via Bluetooth module, and the transmitted data include acceleration, heart rate, and motion gait. After data acquisition, noise elimination is performed by filtering algorithm, and then motion pattern recognition and classification is performed by PSO-SVM algorithm. All test results are compared with manually labeled data to ensure data accuracy. All experiments were conducted under standardized conditions to ensure comparability: participants (ages 12–18, BMI 18–25) performed predefined activities (walking, running, standing, pushing/pulling) in a controlled environment.

Accuracy analysis
Accuracy analysis is the core index to evaluate whether the system can accurately recognize different motion patterns. In order to test the accuracy of the system's motion pattern recognition, we chose four groups of adolescents with different motion intensities for the experiment, and recorded their motion data such as walking, running, standing, and pushing and pulling (as shown in Table 2).

As can be seen from Table 2, the proposed system in this paper has high recognition accuracy in walking and standing modes, and slightly lower recognition accuracy in pushing and pulling and running modes, but still maintains above 95%. The data results show that the proposed system has high accuracy and can effectively recognize different motion modes.

To provide a comprehensive evaluation, we compared the proposed PSO-SVM algorithm with more recent motion classification methods: Convolutional Neural Networks (CNN)[26] and Long Short-Term Memory

(LSTM)[27]. The experiments were conducted under identical conditions, with adolescents aged 12–18 performing four predefined activities: walking, running, standing, and pushing/pulling. The results, summarized in Table 3, highlight the superior performance of PSO-SVM in terms of accuracy, response time, and computational efficiency.

As shown in Table 3, the proposed PSO-SVM algorithm consistently outperformed CNN and LSTM across all metrics. For walking and standing, PSO-SVM achieved 97.5% and 96.7% accuracy, respectively, compared to 94.8% and 93.5% for CNN, and 93.2% and 90.8% for LSTM. The superior accuracy of PSO-SVM is attributed to its efficient hyperparameter optimization and adaptability to high-dimensional motion data. In terms of response time, PSO-SVM demonstrated an average latency of 230 ms, significantly lower than CNN (350 ms) and LSTM (420 ms). This improvement is critical for real-time health monitoring applications, where timely feedback is essential.Additionally, PSO-SVM exhibited lower resource usage, requiring only 50 MB of memory and 120 mW of power, compared to 75 MB/180 mW for CNN and 90 MB/210 mW for LSTM. This efficiency makes PSO-SVM more suitable for wearable devices with limited computational capabilities.

Response time and real-time analysis

Response time and real-time are the key factors to measure the effectiveness of the system's feedback in real-time training. During testing, we calculated the average time from sensor acquisition to data feedback and tested it under different network conditions to ensure the system's responsiveness in various environments. The test results are shown in Table and Fig. 7.

System loadability test

System loadability is one of the indicators of system application performance. Carrying capacity and scalability determine the feasibility of the system in large-scale applications. For this reason, we simulate a scenario in which multiple adolescents use the system at the same time. Taking functional training as an example, the system of literature[28], the system of literature[29] and the system of literature[30] are used as the comparison systems, and the four systems test the completion rate of adolescent functional training in 35s with different numbers, and the results are shown in Table 4.

Analyzing Table 4, we can see that the training completion rates of this paper's system are above 96% with the increase of the number of athletes in the simulation scenarios within a fixed period of time, and the decreasing trend is small. The training completion rate of the other three comparison systems gradually decreases when the number of athletes increases. The experimental results show that the present system has excellent load-bearing properties, and the system performance remains stable even if the number of trainers in the simulation environment increases.

The superior loadability performance of our proposed system compared to existing systems[26–28] can be attributed to several key algorithmic and infrastructural innovations.

(1) PSO-SVM Algorithm: The integration of Particle Swarm Optimization (PSO) with Support Vector Machines (SVM) represents a significant advancement in motion pattern recognition. Unlike traditional SVM models that require meticulous parameter tuning, our PSO-SVM algorithm optimizes the penalty parameter C and kernel parameter a through particle swarm optimization, enhancing classification accuracy and reducing overfitting risks. This optimization process is computationally efficient, allowing the system to maintain high recognition accuracy even under high user loads.
(2) Efficient Data Preprocessing: The system employs advanced filtering techniques, including the use of a hysteresis comparator circuit for noise reduction, which minimizes data transmission interference and ensures data accuracy. This preprocessing step reduces the computational load on subsequent data analysis stages.
(3) Optimized Sensor Deployment: The strategic placement of MEMS sensors at the waist and thighs captures the most informative motion data while minimizing noise from high-frequency movements of distal segments. This optimal sensor placement reduces the amount of data that needs to be processed without sacrificing information richness.

Metric	PSO-SVM	CNN [26]	LSTM [27]
Accuracy (%)			
Walking	97.5	94.8	93.2
Running	95.3	92.1	89.5
Standing	96.7	93.5	90.8
Pushing/Pulling	96.1	88.7	87.3
Response time (ms)			
Average	230	350	420
Maximum	250	400	500
Resource usage			
Memory (MB)	50	75	90
Power consumption (mW)	120	180	210

Table 3. Comparison of motion classification algorithms.

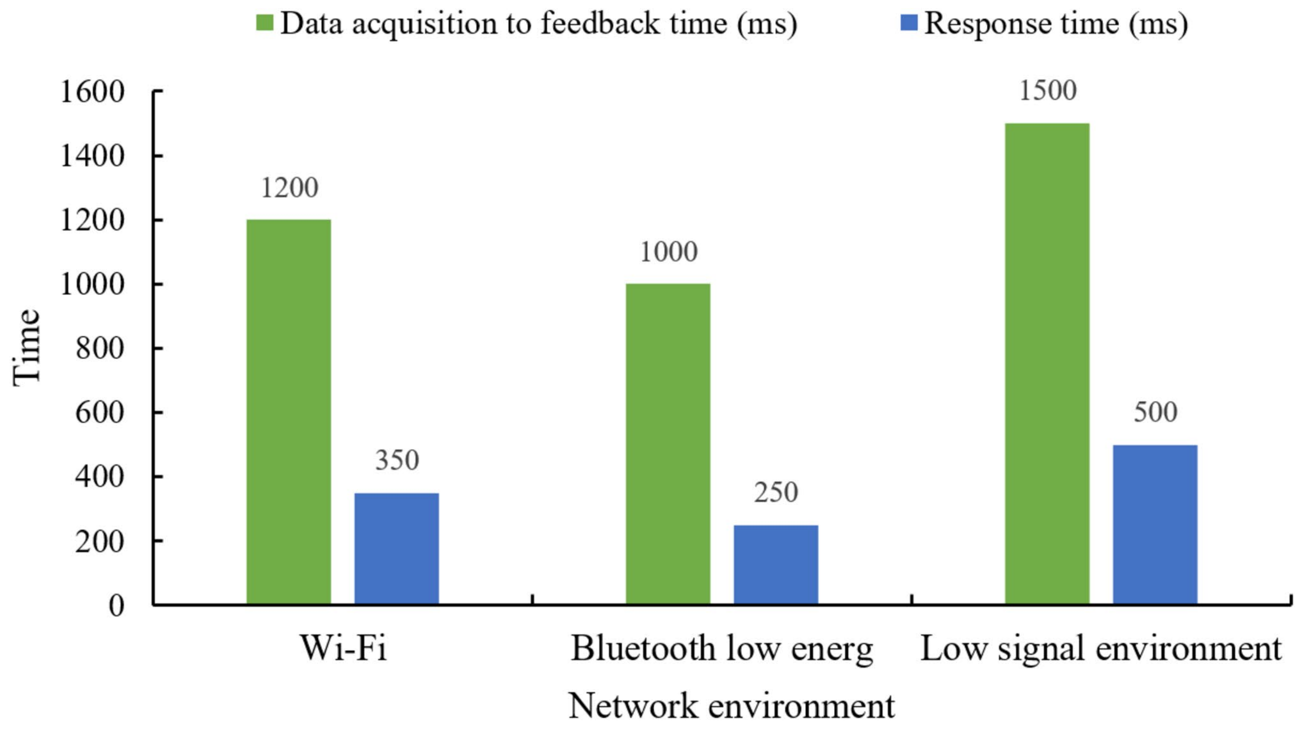

Fig. 7. System response time under various network conditions.

Number of adolescents	Proposed	Literature[28]	Literature[29]	Literature[30]
100	98.1	93.9	90.3	85.3
200	97.8	87.4	86.7	81.0
300	96.6	90.3	86.7	77.7
400	96.4	80.5	80.4	71.6
500	97.9	80.5	80.9	65.5
600	96.2	76.2	76.9	58.1

Table 4. Four system loadability test results.

(4) Hierarchical Algorithm: The hierarchical approach to feature extraction and classification improves processing efficiency. By categorizing signals into static and dynamic patterns first, the system can more quickly extract features using angular velocity sensor analysis, reducing the overall computational burden.

Under high user loads, traditional systems suffer from exponential increases in latency and memory usage due to unoptimized algorithms (e.g., CNN/LSTM) and full-body sensor deployments. In contrast, our system's streamlined architecture and PSO-SVM efficiency ensure stable performance.

Application test

In order to test the application effect of the system in this paper, adolescent patients in the rehabilitation department of a large general hospital were selected as experimental research subjects. Four basic rehabilitation training programs were used for simulation training, namely balance training, muscle strength training, coordination training and functional training. The four physical training programs of 10 adolescents were tested before and after using the proposed system, and the results were taken as the average of five tests, as shown in Table 5.

After analyzing Table 5, it can be seen that the four physical fitnesses of the 10 adolescents were improved to different degrees after applying the system of this paper. This shows that the simulation effect of this system is good, and it can improve the physical fitness of adolescent patients to a certain extent. It verifies the application value of this system in improving the rehabilitation effect of patients.

Discussion

The integration of PSO with SVM represents a significant advancement in addressing the limitations of traditional SVM parameter tuning, particularly in dynamic environments such as adolescent rehabilitation. Traditional SVM models require meticulous manual parameter tuning, which can be time-consuming and

Adolescents number	Balance training (B/A application)	Muscle strength training (B/A application)	Coordination training (B/A application)	Functional training (B/A application)
1	41/64	21/30	130/153	80/50
2	38/57	23/29	118/143	78/83
3	40/61	22/26	121/141	75/80
4	35/52	18/27	119/146	72/77
5	40/54	30/38	124/151	70/75
6	42/65	25/35	125/155	77/82
7	39/58	22/31	117/144	76/81
8	37/55	19/28	120/150	74/79
9	41/63	24/32	123/152	73/78
10	36/56	17/26	116/147	71/76

Table 5. Physical fitness test results before and after using the proposed system. B represents before, A represents after.

suboptimal, especially in high-dimensional motion data scenarios common in rehabilitation settings. The PSO algorithm automates this process by efficiently searching the parameter space to find optimal values for the penalty parameter C and kernel parameter a. This automation not only reduces the risk of human error but also enhances the model's adaptability to diverse and complex motion patterns.

In dynamic adolescent rehabilitation scenarios, the motion data characteristics can vary significantly across different activities and individuals. The PSO-SVM algorithm demonstrates superior performance in such environments due to its ability to dynamically adjust parameters based on the data's inherent structure. This adaptability is crucial for maintaining high recognition accuracy across various motion modes, as evidenced by the system's performance in recognizing walking, running, standing, and pushing/pulling motions with accuracies exceeding 95%.

The proposed IoT-enabled health monitoring system demonstrates significant advancements in real-time motion pattern recognition for adolescent rehabilitation. The system's high accuracy in motion pattern recognition (>95%) and rapid response time (<250 ms) are crucial for real-time health monitoring and feedback. This precision allows for immediate corrections in training form, enhancing safety and effectiveness. The improved physical fitness and rehabilitation outcomes among adolescent patients validate the system's practical utility in healthcare settings.

While the clinical application tests in a large general hospital demonstrated significant improvements in balance and muscle strength among adolescent patients, translating this system into non-simulated rehabilitation settings presents several challenges.

(1) Environmental Variability: Real-world settings introduce uncontrolled variables (e.g., uneven terrain, ambient noise) that may degrade sensor accuracy. For instance, abrupt movements or electromagnetic interference in clinical environments could disrupt data transmission, necessitating adaptive noise reduction algorithms beyond the current hysteresis comparator design.
(2) User Compliance: Adolescents with diverse pathologies (e.g., cerebral palsy, post-traumatic injuries) may exhibit irregular movement patterns or fatigue, requiring personalized calibration and dynamic algorithm adjustments to maintain recognition accuracy.
(3) Device Wearability: Prolonged use of waist and thigh sensors may cause discomfort or skin irritation, particularly for adolescents with sensory sensitivities. Future designs should explore lightweight, hypoallergenic materials to enhance user adherence.

To establish efficacy across diverse pathologies, rigorous clinical validations are essential:

(1) Longitudinal Studies: Multi-year trials tracking rehabilitation progress (e.g., gait symmetry, muscle recovery) are needed to assess the system's sustained impact. For example, a 12-month study comparing IoT-assisted training with conventional methods could quantify long-term benefits.
(2) Control Group Design: Randomized controlled trials (RCTs) should compare outcomes between groups using the proposed system versus standard rehabilitation protocols. Metrics such as Functional Movement Screen (FMS) scores and electromyography (EMG) data would provide objective validation.
(3) Pathology-Specific Testing: The system must be validated across heterogeneous adolescent populations (e.g., obesity-related mobility issues, neuromuscular disorders). Adaptive algorithms, such as pathology-specific SVM kernels or sensor fusion techniques, could address variability in movement patterns.

These steps would ensure the system's robustness and adaptability in real-world clinical practice, bridging the gap between experimental validation and widespread adoption.

Conclusion

This study presents an IoT-enabled real-time health monitoring system designed to enhance adolescent physical rehabilitation through precise motion pattern recognition and personalized feedback. Leveraging MEMS sensors and advanced machine learning techniques, the system addresses the growing need for effective, scalable solutions in youth health monitoring.

The proposed system integrates wearable sensors at the waist and thighs to capture biomechanical data, which is processed using a PSO-SVM algorithm for accurate motion classification. Experimental results demonstrate a recognition accuracy of 95.3–97.5% and a response time consistently below 250 ms, outperforming existing systems such as CNN and LSTM. These achievements highlight the system's potential to improve physical fitness and rehabilitation outcomes for adolescents, particularly in school-based settings where access to quality training is limited.

While our system demonstrates promising performance in controlled experimental settings, several limitations should be acknowledged. Firstly, the system's performance under real-world conditions may vary due to factors such as network latency and sensor misalignment. Network latency can affect the real-time feedback capability of the system, while sensor misalignment may introduce errors in motion data collection. Secondly, inter-individual variability among adolescents can impact the system's recognition accuracy. Differences in body shape, movement patterns, and physical fitness levels may require personalized calibration and adaptation of the system. Addressing these limitations in future work could further enhance the system's robustness and applicability in diverse real-world scenarios.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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J.Y. contribution lies in data analysis, original draft preparation and sorting, J.H. and W.C. participated in the relevant revisions of the section " Experiment and Analysis ". All authors have read and agreed to the published version of the manuscript.

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Declarations

Competing interests
The authors declare no competing interests.

Ethical approval
This research adheres to all relevant data privacy regulations and best practices. The data used in this study is publicly available and authorized for use. No personally identifiable information (PII) of any individual was collected or analyzed. All data handling and analysis were conducted in accordance with ethical guidelines for data privacy and security.

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