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Modeling of Sports Training Simulation Based on Energy Harvesting in Wireless Sensor Networks

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ABSTRACT

For patients with limb motor dysfunction, the effect of physical exercise is directly related to their future quality of life. This article combines the physical training plan of rehabilitation therapists with the training of rehabilitation robots, which can effectively improve the training performance of existing lower limb rehabilitation robots. Therefore, a teaching and training method and a wireless data acquisition system based on energy acquisition wireless network sensor are proposed. Based on wireless wearable technology, wireless network sensors, PCs and electronic devices are used to monitor the activity information of human walking and standing in real time, and the physical fitness is tested by means of mean, variance, and standard deviation. Through the analysis of rehabilitation health, this article consists of two parts: power module and physical exercise. Finally, experiments show that the accuracy of wireless network sensors based on SVM algorithm is the most accurate under physical training. It provides a good means for wireless body area network technology.

KEYWORDS

Energy acquisition, Physical training, simulation model, Wireless sensor network detection

INTRODUCTION

Wireless sensor networks (WSNs) have emerged as a promising technology for sports training simulations, enabling real-time monitoring and analysis of athletes' performance. The integration of WSNs with energy harvesting techniques promotes sustainability by eliminating the need for battery replacements or recharging. In recent years there has been an increasing interest in developing models for sports training simulations based on energy harvesting in WSNs.

Modern society is also marked by global aging, resulting in a significant number of patients with heart and brain diseases. These patients often experience interrupted blood supply to the brain caused by cerebral vascular thrombosis or cerebral vascular rupture and hemorrhage, leading to corresponding movement issues (Wen & Yu, 2021). Recent statistics from China indicate that there are approximately 24.07 million people with physical disabilities in the country. The continuing aging of society will further increase the number of disabled

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individuals. With the development of the social economy, sensory and cognitive functions have been lost or damaged, and the number of people suffering from severe diseases due to aging continues to rise each year (He & He, 2022). Research reports demonstrate that active rehabilitation training for serious disabling diseases, such as heart and brain diseases, can allow 90% of patients to recover their ability to walk and take care of themselves, while 30% of patients can resume some light work. In contrast, without rehabilitation training, the recovery rates for these aspects of life are only 60% and 5%, respectively. Furthermore, the mortality rate in the rehabilitation group is approximately 12% lower than that in the non-rehabilitation group (Zhang et al., 2022).

Type 2 diabetes mellitus (T2DM) is a chronic metabolic disorder that affects millions of individuals worldwide. It is characterized by impaired insulin secretion and insulin resistance, which result in various complications, including liver dysfunction and dyslipidemia. Recent studies have shown that aerobic training and vitamin D supplementation effectively improve liver enzyme levels and lipid profiles in T2DM patients (Hoseini et al., 2022a). Additionally, these interventions have been found to simultaneously modulate inflammatory gene expression and oxidative stress, contributing to the improvement of T2DM (Hoseini et al., 2022b). The COVID-19 pandemic has underscored the importance of health-related factors in the adult population. Physical activity levels, eating behavior, quality of life, general health, and mood states have been identified as crucial elements that influence overall well-being (Rahim et al., 2023). Exercise interventions, such as resistance training, have demonstrated their ability to reduce muscle damage even in non-athletic individuals, suggesting potential benefits for improving fitness levels (Mohammed et al., 2022). Moreover, endurance training and L-arginine intake have been investigated for their effects on antioxidant indices in cardiac muscles, indicating their potential role in cardiovascular health (Saifaddin et al., 2023). Similarly, walking exercise and folate supplementation have been explored for their impact on plasma homocysteine levels in elderly non-athletes (Saifalddin et al., 2023).

Rehabilitation plays a key role in the treatment of motor dysfunction (Cui, 2021). For patients with limb motor dysfunction, the effectiveness of physical exercise directly influences their future quality of life and even the quality of life of the patient's entire family (Jia, 2021). Patients with dyskinesia typically undergo two clinical treatments: drug therapy and physical therapy. Drug therapy stimulates the nerves associated with dyskinesia through various hormones and psychoactive drugs to awaken motor function, while physical therapy is relatively mild and active, gradually regulating motor muscles and nerves through acupuncture, massage, and exercise programs (Gao et al., 2020). However, the current rehabilitation situation in China is characterized by a large number of patients with physical disabilities, a significant shortage of rehabilitation doctors, and a severe lack of high-end rehabilitation medical equipment, particularly advanced intelligent rehabilitation equipment for patient physical training. On the basis of clinical experience, rehabilitation doctors conduct rehabilitation training for patients using methods that are not real-time, lack subjectivity, and are cost-prohibitive.

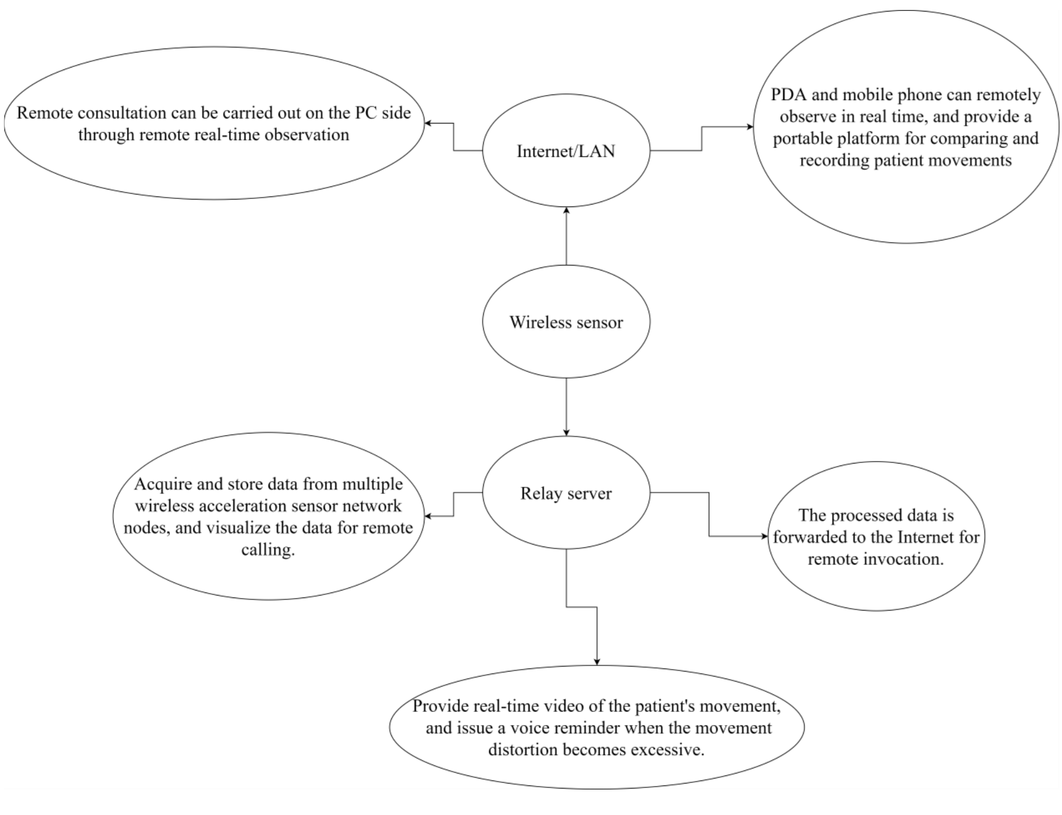
With the development of telemedicine, microsensors, and other technologies, there is an increasing focus on remotely guiding, monitoring, and managing home rehabilitation for the elderly and patients with chronic diseases using wireless somatic sensor networks composed of multiple microsensors (Idrees et al., 2016). Generally, this network consists of a data acquisition node with wireless communication functionality and a network coordinator. Wireless sensors possess biomechanical characteristics that allow for testing and rehabilitation of sensors distributed in different parts of the human body (Dai et al., 2022). Employing various *instruments worn on the bod*y keeps the power consumption based on wireless sensors relatively low, making them highly valuable for monitoring human movement. Additionally, the sensors are sensitive and hold significant value for physical training (Lin et al., 2022).

FUNCTION CONSTRUCTION OF PHYSICAL TRAINING DETECTION

The WSN system for sports rehabilitation described in this paper will eventually be applied to the sports rehabilitation of patients with movement disorders. In traditional physical training, there are many problems associated with the use of wireless devices on the human body. The training mode of the equipment is difficult for patients to understand, the value of the sensor for obtaining motion parameters is not perfect, and the combination of physiological parameters and motion adoption numbers is not complete in the analysis of motion adoption numbers. Therefore, in the analysis of different patients' physical conditions, wireless sensors need to obtain accurate parameters of patients and conduct comparative analysis. Through the preliminary processing of the latest data, we can analyze the different requirements of physical training (Ertz et al., 2022). Please refer to Figure 1. The architecture of this system is divided into three main parts: wearable wireless acceleration sensor network, relay server, and data processing terminal.

Among these, the relay server is the core of the system. As the relay node of the on-site WSN, it is responsible for receiving the motion data from each node, formatting the data into various local data visualization formats, frame formats sent to remote terminals, local data storage formats, and formats matching with real-time video streams. It can better complete the evaluation effect of doctors' online rehabilitation (Palumbo et al., 2021). There are also data processing terminals, which are divided into local terminals and remote terminals.The local terminal can move and display data storage, and alert for non-standard actions; the remote terminal is an intelligent terminal that can remotely obtain patient motion data and patient motion video through various network media and can view patient body data and body data storage. The system can support PC, PDA, and mobile phones as

Figure 1. Schematic diagram of assisted rehabilitation



data terminals, which can free physical training from constraints of time and place, and truly realize the physical training monitoring of a WSN. Figure 2 and Figure 3 illustrate the composition of local terminal and remote terminal monitoring software.

The recovery process in sports rehabilitation requires the supervision and guidance of family members and psychologists. Different patients' exercise parameters are often different. Because of different real-time network psychological parameters, different health monitoring and rehabilitation plans are needed for the analysis of patients' psychological parameters. At the same time, the rehabilitation plan should be formulated according to the patient's exercise parameters (Yang & Lv, 2020). Therefore, the system is required to have real-time capability, accuracy, security, stability, and

Figure 2. Composition diagram of local terminal monitoring software

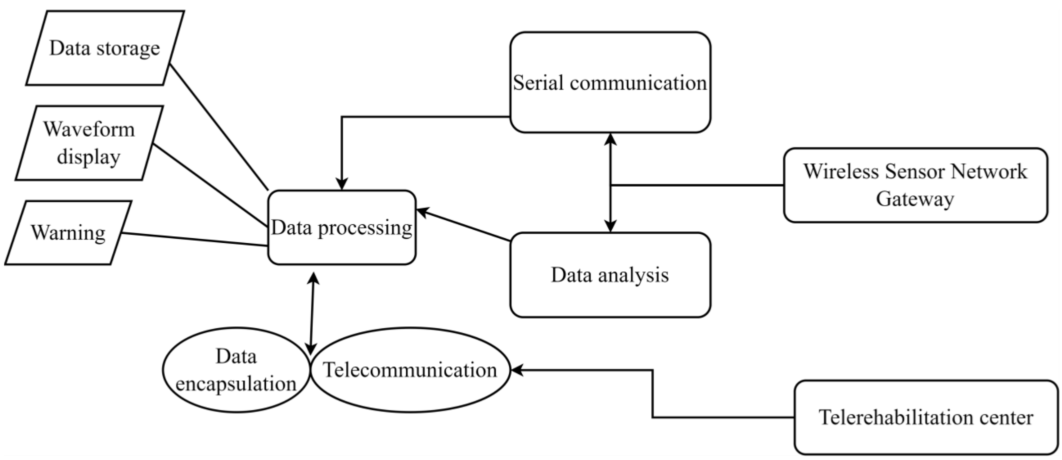
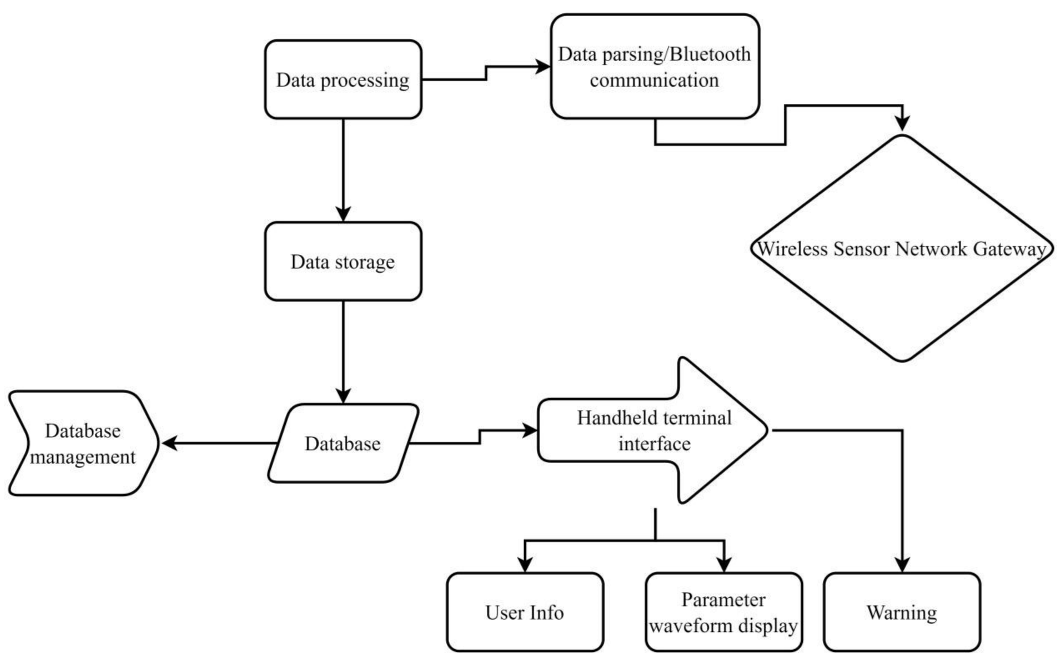


Figure 3. Composition diagram of remote terminal monitoring software



low power consumption. The sensor node takes "relay server" or "field data acquisition terminal" as the central node, using the system's ability to increase and decrease nodes conveniently, so as to meet the physical training needs of different parts and different ranges, all of which is needed to meet the requirements of human body data collection, processing, and transmission. The key factors that specifically constitute wireless sensing are as follows. First, the equipment should be small and portable, allow movement, and make minimum impact on the body, and the parts in contact with the body should be made of non-irritating materials. Second, the equipment should not be used if it is damaged. It has an impact on the patient's body and can use the IEEE802.15.6 protocol frequency that is consistent with the Wi-Fi frequency. Third, the patient needs to perform sports physical training, and the equipment must not have a communication shadow during this process. Fourth, the system must provide a remote interface, which allows the patient to do physical training at home, allows doctors to obtain real-time data and video remotely, and allows for online consultation (Jian et al., 2017). Fifth, the device described in this paper has low power consumption and can work for a long time without having the battery replaced. Sixth, the system must be able to recognize and analyze the voices of patients to facilitate the use of nodes. Finally, in case the patient has adverse reactions during the use of the device or during physical training, the device should have an alarm function.

FUNCTIONAL HARDWARE AND SOFTWARE DESIGN OF PHYSICAL TRAINING MONITORING SYSTEM

Software Function Design Algorithm of the Physical Training Monitoring System

Feature extraction methods are diverse. For different behavior recognition, researchers will extract different behavior data eigenvalues. For example, when identifying static (e.g., standing, sitting) and dynamic (e.g., walking, running) behaviors, the most obvious difference between the two types of behaviors is the fluctuation amplitude of the acceleration signal. Therefore, researchers will extract features such as variance and standard deviation that can reflect the fluctuation amplitude of data. When identifying motions associated with danger—i.e., the motion of falling—the acceleration value of the patient at the moment of falling will change sharply; its peak value will be much higher than that under normal behavior (Landaluce et al., 2020). At present, the feature selection algorithms commonly used for this function are the behavior recognition algorithm and the pattern recognition algorithm (Hu et al., 2022).

Let's first look at the following support vector machine algorithm. The real result is called empirical risk, $R_{emp}\left(w\right)$. In order to meet the principle of empirical risk minimization, it is necessary to choose a sufficiently complex classification function that when the VC dimension is high, it can accurately remember each sample, but the data outside the sample will always be classified incorrectly. Then the expression is

$$R\left(w\right) = R_{emp}\left(w\right) + \varphi\left(n / h\right) \tag{1}$$

y_i is a category marker. When $y_i = +1$ is positive, $y_i = -1$ is negative. Then, it is assumed that the data set T is linearly separable. Let the separation hyperplane H separate these two kinds of samples, then the expression is

$$w \bullet x + b = 0 \tag{2}$$

The geometric interval expression that defines the sample point $\left(x_i, y_i\right)$ to the separation hyperplane is

$$\gamma_i = y_i \left(\frac{w}{\|w\|} \bullet x_i + \frac{b}{\|w\|} \right) \tag{3}$$

therefore, expressed as

$$\gamma = ^{\min}{}_{i=1,2,\ldots,n}\ \gamma_i \tag{4}$$

Bayesian reasoning is a probability learning method based on a priori probability and observation value. It obtains the calculation expression of a posteriori probability of each type of observation value mainly through conditional probability:

$$P\left(h \middle| D\right) = \frac{P\left(D \middle| h\right) P\left(h\right)}{P\left(D\right)} \tag{5}$$

$P\left(h\right)$ refers to the initial probability assumed by h before there is no training data; the data point D is observed without any assumptions. $P\left(h \middle| D\right)$ is the a posteriori probability, that is, the probability that D is established when h is given.

BP neural network has shown good classification ability in electrical signal pattern recognition (Mohamed et al., 2018). BP neural network follows the learning rule of gradient descent. Its core idea is to propagate the input forward layer by layer and the error backward layer by layer. By using the error, the thresholds of the network are constantly adjusted, so that the actual output is as close as possible to the expected output, thus achieving the purpose of BP neural network classification. One part of all the sample data is used for network training, and the other part is used for testing the classification effect. Assuming that there is an output layer, the number of hidden layer nodes is expressed as follows:

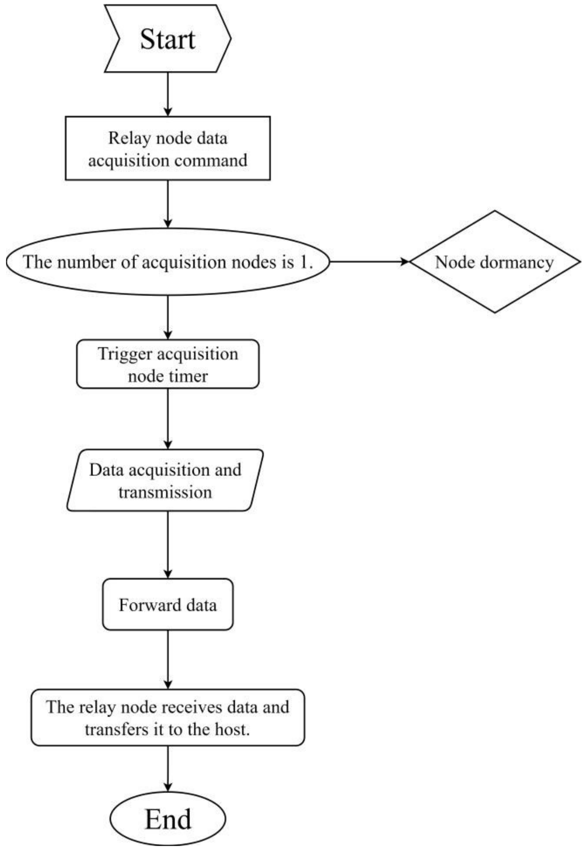
$$\begin{cases} m = \sqrt{n + l + a} \\ m = \log_2 n \\ m\sqrt{nl} \end{cases} \tag{6}$$

BP neural network is a learning algorithm that modifies network parameters through error back-propagation, so it is also called a back-propagation algorithm. If the output cannot reach the set output range, the error will be calculated by a gradient descent learning algorithm, and the weight value and threshold between each neuron will be adjusted, so as to continuously optimize the network model to obtain the expected output (Derakhshan & Yousefi, 2019).

$$T_1 = T_2 \cdot T_3 \tag{7}$$

As shown in Figure 4, the WSN system can realize the specific flow chart of data acquisition, forwarding, and receiving

Figure 4. The WSN system can realize the specific process of data acquisition forwarding and receiving



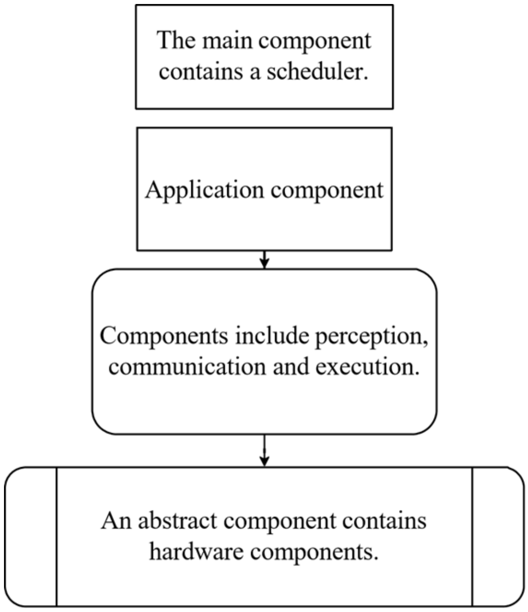
Sending a signal at the relay node can trigger the timer. The technician must find the timer according to their own node, send the collected data, forward it, transmit it to the relay point again, and transmit the data to the user through serial communication. Through the analysis of different components, different editing procedures are developed. This paper constructs the component analysis value of open-source technology. Various grid-embedded frameworks are used to analyze the structural operation. The development applications of different foundations are summarized. Figure 5 is a design diagram of the operating structure.

As can be seen in Figure 5, each layer structure is composed of different components, in which abstraction is the abstraction of physical hardware into a system model. The application component is a unique application program provided for users. On the basis of abstract components, the system realizes the simulation of node sensing, execution, and communication functions. The abstract component is the main call portal of the system, which contains various schedulers. Each group of components is composed of a series of commands and various events, which are connected by interfaces, and the upper component sends commands to the lower component in turn, thus realizing the function of quickly monitoring the rehabilitation of sports injuries (Wang et al., 2018).

Hardware Function Design of the Physical Training Monitoring System

The wireless acceleration sensor network node is composed mainly of five components, namely the power supply system, the RF module, the high-performance processor, the low-power controller, and the sensor (Gong & García-Díaz, 2022). Simple peripheral circuit and analog output can be

Figure 5. Operating structure



easily combined with microcontroller (Zhu et al., 2014). The microcontroller and the low-power controller constitute the acceleration value acquisition unit. The operating current is lower than the current during sleep mode. Therefore, the working pin of the low-power controller can be used to supply power to the sensor at a high level. During the sleep period, setting the working pin to a low level can completely turn off the sensor power supply (Yin et al., 2021). The microcontroller and the low-power controller constitute acceleration value acquisition unit. Then its calculation method is expressed as follows:

$$R = \begin{bmatrix} \cos\theta\cos\psi & \sin\varphi\sin\theta\cos\psi - \cos\varphi\sin\psi & \cos\varphi\sin\theta\sin\psi + \sin\varphi\sin\psi \\ \cos\theta\sin\psi & \sin\varphi\sin\theta\cos\psi + \cos\varphi\sin\psi & \cos\varphi\sin\theta\sin\psi - \sin\varphi\sin\psi \\ -\sin\theta & \sin\varphi\cos\theta & \cos\varphi\cos\theta \end{bmatrix} \tag{8}$$

$$\frac{dr(t)}{dt} = \omega(t) \times r(t) \tag{9}$$

$$r(t) = r(0) + \int_0^t d\theta(t) \times r(t) \tag{10}$$

$$r_{GSC}(t + dt) = r_{GSC}(t) + r_{GSC}(t) \times d\theta(t) \tag{11}$$

It can be concluded that the diagonal matrix of 1 is

$$R(t + dt) = R(t)\begin{bmatrix} 1 & -d\theta_z & d\theta_y \\ d\theta_z & 1 & d\theta_x \\ -d\theta_y & d\theta_x & 1 \end{bmatrix} \tag{12}$$

Finally we get

$$\begin{aligned}\theta_z &= -\sin^{-1}\left(R\left[3,1\right]\right)\\ \varphi_Z &= \tan^{-1}\left(R\left[3,2\right] / R\left[3,3\right]\right)\\ \psi_z &= \tan^{-1}\left(R\left[2,1\right] / R\left[1,2\right]\right)\end{aligned} \tag{13}$$

The radio frequency module is the most important component for the realization of wireless communication. This design selects the company's RF chip, which fully meets the standard. This versatile, two-way transceiver with a data modem can be used in technical applications (Lorincz et al., 2009). The power system design of the WSN nodes directly affects the power consumption of the nodes, thus affecting the life cycle of the nodes. In order to meet the dual needs of actual use and testing and debugging, we designed U2: cyt1173. When the node is in actual use, the 3V low voltage differential regulator is not welded. The system is powered by an external 3.3V lithium battery and connected by Vin. It is short circuited with VB and V3 through the shaped filter circuit composed of C1, L1, and C2 to supply power to the system. When the node is in the test and commissioning stage, welding U2: cyt11, VIN can be connected to the external power supply of 4.5V ~ 7V, which is stabilized from cty117 to 3.3V for the use of the system. In order to make it easy to wear and provide for the impact of the package on the RF system, the outer package of the node is worn in the form of a wrist guard. Finally, the power consumption test results are shown in Table 1.

Dual-core architecture has better sleep function than single-core architecture, which is one of the keys to reducing power consumption. After the device is powered on, the internal program of the node is initialized, the nodes in the network organize themselves, and the preparation process for entering the sleep state begins. The low-power microcontroller plays a major role in the whole sleep process (Rault et al., 2014). The low-power controller will wake up in seconds. After being awakened, it will enter the radio frequency communication state if it meets the network synchronization time point; if it does not meet the synchronization time point after being awakened, it will complete the data acquisition and caching of the sensor once. After the data acquisition is completed, the node performs the sleep operation again and enters the sleep state. In the working process of the node, the sleep period is, while the activity period with relatively high-power consumption is only one, so the power consumption can be greatly reduced (Darwish & Hassanien, 2011). The large original ECG signal is accompanied by a large amount of noise, which causes difficulty in meeting the quality

Table 1. Single and dual core power consumption test results

Architecture	Single core processor	Single core processor 1	Dual core processor
Protocol implementation	Unable to implement full agreement	Can	Can
Sleep cycle	$< 8s\,@\,3.1\mu A, 1.86V$	$< 1.3s\,@\,2.1\mu A, 1.86V$	$< 8s\,@\,3.2\mu A, 1.86V$
Sleep power consumption μW	5.6	3.8	6.2
Activity cycles	65–100	30–55	25–50
Active power consumption μW	2.45	5.89	6.46
RF power consumption μW	55.84(send and receive every 62s)		
Average power consumption μW	102.4	216.8	68.2

requirements. According to the characteristics of the ECG signal for hardware filtering. The ECG signal is concentrated mainly between 0.1Hz and 100Hz, so the cut-off frequency of the low-pass filter is 100Hz, and the high-frequency noise above 100Hz is filtered out; at the same time, the cut-off frequency of the high-pass filter is 0.05Hz, and the low-frequency noise below 0.05Hz is filtered out. The Bluetooth module in the wireless sensor is the key to the near-end monitoring software. The module itself is connected to the node, so the module is required to be miniaturized and integrated. The module designed in this system uses the Blue Core4-Ext chip, which is small and easy to carry.

EXPERIMENTAL SYSTEM TEST

The first requirement for this experiment was the participation of two technicians who knew the experimental rules and used the experimental equipment, as well as a rehabilitation therapist with many years of clinical experience. The therapist divided patients A, B, C, and D into Brunnstrom stages and recorded the general data of the patients, then explained the process and purpose of the experiment to the patients' families and the patients themselves. Finally, the technicians put acceleration sensors on the patients according to the experimental rehabilitation recommendations. To ensure the collected data (Raveendranathan et al., 2011). The signal acquisition sensor board in the wireless sensor node designed in this system includes mainly a signal acquisition sensor board, an ECG signal acquisition sensor board, and a motion position acquisition sensor board. The patient computer client was programmed using MATLAB language. The main functions of the patient client were the selection of training programs, the customization of different rehabilitation actions for patients, and the timely adjustment of training subjects according to the degree of recovery. In this experiment, four movements were set for the patient, namely, bridge movement, sit training, stretching hips and knees, and alternately loading the legs for testing; Professional rehabilitation therapists demonstrated the rehabilitation actions, and could automatically switch to the corresponding training for patients. The acceleration curve of the real-time rehabilitation movement indicated that the patient's rehabilitation movement and physical condition could be well known. The rehabilitation action scoring system can let patients and rehabilitation teachers know the accuracy of actions and provide assistance for the knowledge of treatment rooms. At the same time, the action score can also motivate patients to keep on refueling. Table 2 provides statistics about the online identification of WSNs.

It can be seen from the statistics table that the average online recognition rate reaches 95.5%, and the overall recognition effect is not as good as the offline recognition rate. There are many reasons for the reduction in the recognition rate, which need to be considered. The fatigue of the muscles, the deviation between the position of the armband and the offline training, and the online recognition is the threshold set by the starting point; all these need to be considered and need to be improved. Improve recognition rate. The current experiment is still conducted by the experimenter. If the experimenter is replaced by a new user, the system needs to be retrained to obtain new weights and thresholds, because each person's muscle structure and strength are different, and they need to be retrained to ensure the recognition rate. The number of training samples for each behavior was reduced

Table 2. Online identification of WSNs

Movement pattern	Motion1	Motion2	Motion3	Motion4	Sterility	Average recognition rate
Motion1	196	0	8	0	4	95.1%
Motion2	0	188	0	9	0	96%
Motion3	8	0	192	0	1	96.2%
Motion4	0	6	0	189	2	96.3%
Average recognition rate						95.5%

from 460 to 128, and the feature matrix was used as training data to build a classification model. The recognition accuracy of abnormal behaviors using SVM, KNN, BP and NB algorithms was analyzed and compared. That is to say, some samples were randomly selected from the original training data sample database to build a small sample database, so as to lose the accuracy of behavior recognition in exchange for recognition speed and save the time of behavior recognition, thus making the process suitable for online abnormal behavior recognition. After reducing the training sample of each behavior to 128, the behavior recognition effect of KNN algorithm was compared with different k values. As shown in Table 3, reducing the training sample to 128 is the recognition effect of KNN algorithm.

It can be seen from the table that when the samples were reduced, the accuracy of behavior recognition using the KNN algorithm to build the classification model were reduced to some extent compared with that in the case of large samples. The accuracy of behavior recognition was the highest when K=11 in the case of small samples, followed by that when K=7, and the results of behavior recognition when K=5 and 9 were relatively poor. Therefore, this article compares the behavior recognition effect of the KNN algorithm with SVM, DT, and NB when K=11. *Large sample* means that 479 samples of each behavior were extracted as training data, while *small sample* means that the training data of each behavior was reduced to 128 samples. We can look at the characteristics of the acceleration curve of the summer solstice rehabilitation exercise of patient C as shown in Table 4.

According to the image analysis of rehabilitation motion acceleration, experimental observation, and previous experience in extracting limb motion features, some features (maximum value, minimum value, peak-to-peak value, mean value, standard deviation, etc.) and sampling features were extracted from the filtered motion signal. These features reflect the completion of the patient's lower limb rehabilitation actions to a certain extent. For example, when the calf was in an upright state, the X axis of the sensor on the calf was $1g$; when the calf was in a horizontal state, the sensor X axis on the calf was $0g$. The sensor's minimum value reflects the limit state of the lower limbs, and the peak-to-peak value reflects the range of motion of the limbs. All the extracted features are as shown in table 4, and the calculation expression of energy features is as follows:

Table 3. Reduction of training samples to 128 is the recognition effect of KNN algorithm

	Four behaviors	Bridge motion	Standing training	Hip and knee extension	Alternating weight bearing with legs
K=5	89.65%	89.77%	99.95%	86.36%	86.56%
K=7	90.12%	88.15%	86.99%	85.86%	99.32%
K=9	86.85%	88.78%	89.54%	86.5%	99.33%
K=11	90.82%	87.95%	90.12%	87.25%	85.32%

Table 4. Characteristics of acceleration curve of lower limb rehabilitation exercise of patient C

Characteristic	Quantity	Describe
Maximum/Minimum value	2*5	Limb movement limit position of lower limb rehabilitation exercise
Peak-to-peak value	1*5	Lower limb rehabilitation exercise limb movement range
Mean	1*5	Average change range of limb posture in lower limb rehabilitation exercise
Standard deviation	1*5	Fluctuation degree of limb posture in lower limb rehabilitation exercise
ENE	1*5	Energy accumulated in XYZ axis of a rehabilitation exercise
Cycle	1	Time required to complete a rehabilitation exercise
Sampling	1*35	General description of rehabilitation action sequence

$$ENE = \sum_{i=1}^{n}\left(\left(x_i^2 + y_i^2 + z_i^2\right)^{\frac{1}{2}} - 1\right) \tag{14}$$

The average was 94.2%. Among them, three times were 100%, all actions were accurately predicted, and seven times were 91.5%. The model predicts one action incorrectly. Because the test set has only 5 subjects and a total of 12 sample data, with the increase in the number of samples in the test set, its recognition accuracy will be lower than 100%, higher than 91.6%, and stable at a fixed value. Let's examine Table 5, the recognition standard rate of 10 lower limb rehabilitation actions in the patient B test set.

It can be seen from Table 6 that when different algorithms have the best parameters, the accuracy of each model is compared, and it is known from the table that the accuracy of the SVM algorithm is as high as 91.8%. From our measured cases, we can see that the visual data chart accurately records the movement process and clearly presents the data, such as the amplitude and rhythm of limb movements. The system's unique function of recording and playing back accurate movement data will be very helpful to doctors as they quantitatively evaluate rehabilitation effects and adjust physical training plans. Through clinical experiments, doctors have shown that this system is suitable for patients' active physical training and has good adaptability to different types and different parts of physical training.

CONCLUSION

This paper examines the current development status and limitations of existing medical-assisted rehabilitation systems. It proposes and implements a comprehensive medical-assisted rehabilitation system that incorporates remote measurement and control technology, utilizing a cross-platform intelligent terminal. The paper introduces innovative concepts, including a dual-core wireless sensor node and a networked approach to detection and physical training. Additionally, it establishes a WSN specifically designed for medical rehabilitation purposes. Experimental tests were conducted to monitor physical training progress. Two wireless network sensors were utilized to record dynamic data during four distinct lower limb rehabilitation movements. Subsequently, 128 features indicative of lower limb rehabilitation movement were extracted and automatically recognized using a neural network algorithm. Experimental results from four test sets demonstrate a comprehensive accuracy rate of 91.8% for recognizing rehabilitation movements.

Wireless network sensor-based physical training represents a burgeoning research area that has witnessed unprecedented growth. However, several challenges remain. Currently, research in human physical training utilizing wireless network sensing predominantly concentrates on simple behaviors within limited environments, making it relatively challenging to identify complex behaviors.

Table 5. Identification standard rate of 10 lower limb rehabilitation actions in patient B test set

Serial number	1	2	3	4	5	6	7	8	9	10	Mean
Accuracy%	91.5	91.4	96.2	100	94.5	91.8	94	96.2	92.1	94.2	94.5

Table 6. Comparison of accuracy of optimal parameters of different algorithms

Algorithm	KNN	SVM	BP
Accuracy%	86.3	91.8	91.2

Furthermore, there is a lack of practical application and extensive research in online recognition of physical training utilizing WSN technology. The WSN proposed in this paper has the capability to effectively monitor multiple physiological parameters and facilitate physical training.

DATA AVAILABILITY

The figures and tables used to support the findings of this study are included in the article.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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