Design of Remote Monitoring System for Limb Rehabilitation Training Based on Action Recognition

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\textbf{Abstract.} Aimed at the high cost of domestic rehabilitation medical care, the limited number of doctors, the shortage of training venues, and the lack of follow-up tracking for patients who recovered better after rehabilitation training, and a remote monitoring system to understand the patient's rehabilitation situation, a kind of motion recognition-based Remote monitoring system for physical rehabilitation training based on motion recognition was proposed. From the perspective of machine learning and intelligent classification, the system uses the wavelet transform principle and Support Vector Machine (SVM) algorithm to inject intelligence into the remote monitoring system for limb rehabilitation training, so that doctors can receive patients walking and running energy characteristic and their movement distance data in the rehabilitation center, and based on this data to determine the patient's recovery and rehabilitation training plan, the doctor can make a diagnosis for dozens or even hundreds of patients even if they never leave home, which greatly improves the efficiency of treatment, saves the corresponding manpower and material resources for the country and society, and benefits the people.

1. Introduction
These Most patients will go to the rehabilitation training center for rehabilitation exercises, and there will be corresponding doctors to guide them in the rehabilitation training center, but it will incur high costs. At the same time, the size of the venue and the number of doctors in the rehabilitation training center also limit the quantity and efficiency of the treatment of patients. Physicians can only provide targeted guidance to a small number of patients, especially for patients who have been able to perform their own rehabilitation training but lack of the venue and timely guidance of doctors, so a set of limbs that can be remotely monitored is urgently needed. Rehabilitation training system. In this way, the lack of space in the rehabilitation center can be solved. The patient can choose training occasions at home and in the park. At the same time, the doctor can receive the patient's walking and running data and the distance of movement in the rehabilitation center. It is the basic data to judge the patient's rehabilitation situation and formulate the next rehabilitation training plan. The rehabilitation training center can also establish a database of patient cases, store these data, and then assign them to doctors, so that doctors can observe the data at work or at home, so that they can be targeted without leaving home. Making the next plan for each rehabilitation training patient can greatly reduce the situation of repeated illness due to the failure to track the subsequent rehabilitation. In addition, it also greatly improves the efficiency of
doctors, and making a number of rehabilitation trainers treated, which will benefit the country and people by reducing the social burden. So from the perspective of machine learning and intelligent classification, this paper proposes an innovative, concise and low-cost remote monitoring system for limb training based on motion recognition for the auxiliary system of limb rehabilitation training\textsuperscript{[1,4]}. 

2. System principle

The remote monitoring system for limb training uses wavelet transform extraction algorithm and SVM classification algorithm. Firstly, the real-time data collection is carried out for the movement signals (such as walking, running and standing) of the rehabilitation trainers through the motion information perception module of the lower computer, and preliminary filtering processing is carried out for the collected data through the STM32 minimum system to set the threshold to overcome the interference of noise to the motion recognition; Secondly, the Bluetooth communication module of the lower computer uploads the collected data to the data receiving unit, and the data transmission unit transmits the signal data to the upper computer software analysis system; Thirdly, the host computer software system performs wavelet packet decomposition on the obtained signal data to obtain the distribution characteristics of the motion signal energy in different frequency bands. Different movements of the rehabilitation training personnel will show different energy distributions, so that different motion signals can be extracted. Energy feature vector, the feature vector that distinguishes the action category is sent to the SVM classifier. Through data training and learning, the type analysis of human actions can be obtained, so as to determine the action category of the person, and achieve intelligent determination of the action. In addition, the system software extracts the number of peaks of the Y-axis acceleration signal data as the number of human actions; Finally, the processed data is transmitted to the doctors in the rehabilitation training center, and the doctor can understand the training and recovery of the rehabilitation trainers by collecting basic data information of the personnel’s actions, so as to make targeted guidance for corresponding rehabilitation trainers formulate the next training plan to achieve the right effect and improve the doctor's treatment efficiency\textsuperscript{[5]}. The principle flow is shown in Figure 1:

3. System algorithm

3.1 Extraction method of motion feature based on wavelet packet

To perform wavelet packet feature extraction on human walking signals (including collectively called signals of walking, running, standing, etc.), do the following steps\textsuperscript{[6]}:
(1) Collect motion signals through the motion information sensing module, use $S$ to represent the original signal, and use db06 as the mother wavelet function to perform three-layer wavelet packet transformation on the signal. Use $(i, j)$ to represent the $j$-th node of the $i$-th layer. Among them $i = 0, 1, 2, 3 \ldots N$ , $j = 0, 1, 2, 3 \ldots 2^N - 1$, $S_{ij}$ is used to denote the wavelet decomposition coefficient of the $j$-th frequency band of the $i$-th layer.

(2) Reconstruct the coefficient of the last layer, and get the signal expression as follows:

$$S = S_{i,0} + S_{i,1} + \ldots + S_{i,2^N - 1}$$

(1)

(3) Calculate the sum of the squares of the coefficients in the frequency band 0.39 ~ 18.75Hz from the one to three layers decomposed by the wavelet packet as the energy's feature quantity.

$$E_{ij} = \int |S_{ij}(t)|^2 dt = \sum_{k=1}^{n} |x_{ijk}|^2$$

(2)

The $x_{ijk}$ ($j = 0, 1, 2 \ldots 2^N - 1, k = 1, 2, 3 \ldots n$) in the expression represents the value of each coefficient decomposed by $S_{ij}$.

(4) Using the energy calculated by the above formula as the feature vector, we have the following expression:

$$T = [E_{i,0}, E_{i,1}, E_{i,2}, \ldots, E_{i,2^N - 1}]$$

(3)

(5) The extracted feature vector is normalized, and energy features have different energy differences in different actions when people perform actions. For example, the power spectrum of running is significantly higher than the power spectrum of walking. After normalization, SVM has better classification effect and better generalization. Therefore, let

$$E = \sqrt{\sum_{j=0}^{2^N-1} |E_{ij}|^2}$$

(4)

$$T' = T / E$$

(5)

So far, we have obtained the normalized feature vector $T'$.

3.2. Intelligent motion recognition based on SVM

After extracting the feature vector, we can combine the pattern recognition technology to classify the corresponding person’s actions for different signal features. Combining the situation that may require short-term efficiency in actual use, the possibility of a small sample training set will appear, and SVM is selected as a classifier. SVM has one good generalization ability, and can avoid the local minimum and topology of the neural network. Optimization problem [7,9].

The construction of the SVM classifier uses RBF as the kernel function of the SVM. The function of the kernel function is to project to high dimensions, and then perform linear classification in high dimensions, so that the nonlinear problems in low dimensions can be solved. This is also the essence of SVM to solve nonlinear problems. The RBF kernel function is widely used in classification, and the expression is as follows:

$$K(x_i, x_j) = \exp(-\frac{||x_i - x_j||^2}{2\sigma^2}) = \exp(-\gamma ||x_i - x_j||^2)$$

(6)

In the above formula, $\gamma = -\frac{1}{2\sigma^2}$ and $\sigma$ are used as parameters to control the width of the RBF. The decision function expression is:
\[ f(x) = \text{sgn} \left( \sum_{\text{support vectors}} y_i \alpha_i K(x_i, x) \right) = \text{sgn} \left( \sum_{i=1}^{l} \alpha_i \exp(-\gamma \|x_i - x\|^2) \right) - b \] 

(7)

In the classification process, the standing state is not classified by SVM, because there is no signal output when standing, but some drift signals can be directly determined by setting thresholds in the software. Therefore, the objects classified by SVM become two categories: Walk around, run around\cite{10,12}.

4. Motion analysis experiment
The experimental analysis of the human walking motion signal, the human motion characteristic energy and the results of the SVM classifier were performed. The specific experimental content is described below:

4.1. Signal analysis of walking movement
During a person's walking, the angular velocity, the accelerometer, and the electronic compass would change. And the following experiments were performed on this: walk from south to north, go out the left foot first, wear the sensor on the right foot, and count 32 steps. The experimenter carried a portable computer and transmitted the data to the host computer's acquisition and display system through the serial port. Sampling rate is 50Hz. In order to easily see the waveform, the original X-axis velocity and Y-axis acceleration waveforms in the time period of 20 seconds to 80 seconds are taken out. as shown in Figure 2:

![a. X axis angular velocity](image)

![b. Y axis angular velocity](image)

Fig 2. Time T walk inside the original waveform (T=20~80s).

Through the above experiments, each signal of walking was obtained, and the filtering process was focused on these signals. Because the signal contains a lot of noise components\cite{13}, it will adversely affect the subsequent feature extraction. In order to analyze the signal characteristics, a 5th order Butterworth band pass filter is designed. Filtering the angular velocity information of the X axis, The high-pass cut off frequency is 25Hz, Because a large amount of experimental data shows that men's walking frequency is generally 0.91 to 1.03 Hz, women's walking frequency is generally 0.98 ~ 1.10Hz. So the low-pass frequency of the design filter is 0.5Hz. The X-axis angular velocity after filtering is shown in Figure 3 below:
The X-axis walking angular velocity signal is transformed and analyzed, and its spectrum is shown in Figure 4 below:

![Figure 4: X-axis angular velocity original data of spectrum.](image)

It can be seen from the frequency spectrum that the signal is concentrated in the range of 0 to 5 Hz, which indicates that when a person is walking, his walking frequency is higher in the content of components at 1 Hz, 2 Hz, and 3 Hz, which is in a low frequency band. The energy characteristic vector of the human action can be obtained according to the X-axis angular velocity data.

After filtering the accelerometer on the Y axis, use wavelet transform to extract the peaks of the waveform to detect the number of steps of the person. The filtered wave peak extraction is shown in Figure 5 below:

![Figure 5: Y-axis accelerometer data filtering wave extraction.](image)

The number of peaks is 32, and the number of steps taken by the personnel in this experiment is also 32. This conclusion proves that the change in the Y-axis of the accelerometer can be used to determine the number of steps taken by the person.\cite{14}
4.2. Personnel motion characteristic energy analysis
Filtering the collected data can better perform feature extraction on the data, and SVM is used to
determine the standing state. Because there will be no solution, it will be determined to naturally enter
the standing state when there is no solution. For other states, the analysis is performed from the energy
perspective, and the aforementioned method of extracting motion feature quantities based on wavelet
packets is used, and the features are extracted and normalized. The characteristics of 10 testers under the
same action were collected in the experiment, as shown in Table 1 below:

Table 1. The energy distribution of the characteristic personnel action.

| Action state | frequency band 1 | frequency band 2 | frequency band 3 | frequency band 4 | frequency band 5 | frequency band 6 | frequency band 7 |
|--------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| Walking      |                  |                  |                  |                  |                  |                  |                  |
| Person 1     | 0.44729          | 0.83159          | 0.06775          | 0.28241          | 0.01265          | 0.05346          | 0.03972          |
| Person 2     | 0.32046          | 0.87956          | 0.05101          | 0.22977          | 0.04298          | 0.05466          | 0.03107          |
| Person 3     | 0.43987          | 0.94961          | 0.06547          | 0.15923          | 0.01674          | 0.04896          | 0.02804          |
| Person 4     | 0.38071          | 0.91273          | 0.06294          | 0.12098          | 0.01073          | 0.04096          | 0.02193          |
| Person 5     | 0.45091          | 0.95008          | 0.06792          | 0.25247          | 0.01431          | 0.06561          | 0.04324          |
| Person 6     | 0.44785          | 0.83951          | 0.06655          | 0.29251          | 0.01237          | 0.05504          | 0.03853          |
| Person 7     | 0.31915          | 0.85005          | 0.05022          | 0.23177          | 0.04348          | 0.05476          | 0.03071          |
| Person 8     | 0.44087          | 0.95321          | 0.06553          | 0.16003          | 0.01669          | 0.04913          | 0.02794          |
| Person 9     | 0.37971          | 0.91372          | 0.06184          | 0.12185          | 0.01082          | 0.04125          | 0.02155          |
| Person 10    | 0.46101          | 0.94808          | 0.0682           | 0.25347          | 0.01415          | 0.06514          | 0.04334          |

| Running      |                  |                  |                  |                  |                  |                  |                  |
| Person 1     | 0.37795          | 0.80035          | 0.27792          | 0.36357          | 0.13468          | 0.17149          | 0.29332          |
| Person 2     | 0.25633          | 0.74746          | 0.25153          | 0.50234          | 0.15093          | 0.13187          | 0.28108          |
| Person 3     | 0.33816          | 0.75461          | 0.22926          | 0.39326          | 0.12594          | 0.22184          | 0.20644          |
| Person 4     | 0.31583          | 0.76482          | 0.27097          | 0.50412          | 0.20014          | 0.22306          | 0.33908          |
| Person 5     | 0.40715          | 0.64810          | 0.20049          | 0.26965          | 0.24684          | 0.33903          | 0.36359          |
| Person 6     | 0.38725          | 0.80015          | 0.27822          | 0.3657           | 0.13568          | 0.17084          | 0.29232          |
| Person 7     | 0.25333          | 0.74846          | 0.25163          | 0.50174          | 0.15103          | 0.13297          | 0.28078          |
| Person 8     | 0.33726          | 0.75631          | 0.22856          | 0.39166          | 0.12604          | 0.22284          | 0.20754          |
| Person 9     | 0.31763          | 0.76662          | 0.27147          | 0.50322          | 0.20114          | 0.22508          | 0.33874          |
| Person 10    | 0.40262          | 0.64527          | 0.20061          | 0.26708          | 0.24725          | 0.33887          | 0.36604          |

As shown in the table above, when people do the same action, they have a great similarity in the
energy distribution, but there are some differences in the energy distribution of different actions. When a
person is walking, as shown in Figure 6, the energy is mainly distributed in the low frequency band, and
higher in the frequency bands 1, 2, and 4.

In order to enhance the generalization of small samples, the penalty factor is adjusted as small as
possible.

Of course, in the initial stage of parameter selection, some parameter optimization methods were
used. Through the genetic parameter optimization algorithm, the optimal parameters shown in Figure 7
below were obtained:
When people are running, it can be seen from the analysis that the energy starts to move to the high frequency band, the high frequency components decomposed by the wavelet packet begin to increase, and the energy starts to increase significantly in the 3, 5, 7 and other frequency bands. The above is an analysis and discussion of the results of different movement energy distributions of personnel, and illustrates that the method of feature quantity extraction can determine the behavior pattern of personnel.

4.3. Analysis of SVM classifier results

The system uses support vector machines for classification, and selects a set of experimental data to test the classification results of SVM.

Here, the parameter penalty factor is \( C = 2.6762 \), the parameter in the RBF function. After experiment, it is found that the parameter \( \gamma = 31.1671 \) is too large, so it is appropriately adjusted to \( \gamma \), which does not affect the accuracy of the classification result\(^{15}\).

After applying the above parameters, a classification model is obtained. Here, 51 support vectors are obtained from the experimental data, including 24 support vectors for walking action and 27 support vectors for running action. The classification accuracy is 100%.

A set of test data is used to verify the accuracy of the classification. In order to better explain the problem, the ROC curve is used as an index to evaluate the classification results. The classification result of the test data is accuracy rate = 96.6667% (58/60) (classification). The ROC curves of the four classifications are plotted as shown in Figure 8:

The ROC curve is a curve drawn according to a series of different cutoff values or decision thresholds. The vertical axis represents the true class rate and the horizontal axis represents the false positive class rate. The closer the ROC curve is to the upper left corner, the better the classification effect or parameter selection this time. It can be seen from the curve that the classification of action 2 in the classification result means that there was a wrong classification of running, but other classification
results are still very satisfactory. Not only can people's actions be recognized, but also maintain a certain accuracy\cite{16}.

Through the above experimental analysis, it is enough to prove that the characteristic amount of the person's action energy can be obtained based on the X-axis angular velocity data, and then the intelligent classification of the SVM is used to determine the action type, and then the number of actions is obtained based on the Y-axis acceleration data, so as to obtain the self-rehabilitation training personnel. Energy feature vector during training. The doctor can compare the energy feature vector of the normal population with the previous energy feature vector of the patient and add medical judgment to guide the patient's subsequent rehabilitation training. And timely detection of signs of repeated illness, so as to avoid secondary harm to the patient, has the purpose of not only preventing repeated illness but also remotely guiding the patient to the next rehabilitation training, which reduces medical costs for patients and the country. Doctors also can guide more patients faster, better and more effectively.

5. In conclusion
Wavelet packet feature extraction and SVM classification algorithm were applied to remote monitoring system for limb rehabilitation training, and a remote monitoring system for limb rehabilitation training based on human motion recognition, machine learning, and intelligent classification was designed. The entire system depends on the triaxial angular velocity meter, triaxial accelerometer, Bluetooth module, single-chip microcomputer system, LabVIEW and MATLAB software. The price is low and affordable for the average family. At the same time, the remote monitoring system for limb rehabilitation training can extract the energy feature vector of the patient's walking and running. The doctor can use this as a reference to understand the patient's recovery and facilitate the formulation of the next rehabilitation training plan.

References
[1] Buckthorpe Matthew, Della Villa Francesco, Della Villa Stefano, Roi Giulio Sergio. On-field Rehabilitation Part 1: 4 Pillars of High-Quality On-field Rehabilitation Are Restoring Movement Quality, Physical Conditioning, Restoring Sport-Specific Skills, and Progressively Developing Chronic Training Load.[J]. The Journal of orthopaedic and sports physical therapy, 2019, 49(8):565-569.
[2] The Impact of Upper Limb Training with Breathing Maneuver in Lung Function, Functional Capacity, Dyspnea Scale, and Quality of Life in Patient with Stable Chronic Obstructive of Lung Disease[J]. Open Access Macedonian Journal of Medical Sciences, 2019, 7(4):567-572.
[3] Gambardella Claudio, Brusciano Luigi, Del Genio Gianmattia, Tolone Salvatore, Terracciano Gianmattia, Gualtieri Giorgia, Lucido Francesco Saverio, Docimo Ludovico. Predictive parameters to identify incontinent patients amenable for rehabilitation treatment: the muscular synergies evaluation.[J]. Arquivos de gastroenterologia, 2019, 56(4):362-367.
[4] Butz Catherine, Iske Cindy, Truba Natalie, Trott Kristen. Treatment of Functional Gait Abnormality in a Rehabilitation Setting: Emphasizing the Physical Interventions for Treating the Whole Child.[J]. Innovations in clinical neuroscience, 2019, 16(7-08):479-483.
[5] Aprile Irene, Germanotta Marco, Cruciani Arianna, Loret Simona, Pecchioli Cristiano, Cecchi Francesca, Montesano Angelo, Galeri Silvia, Diverio Manuela, Falsini Catuscia, Speranza Gabriele, Langone Emanuele, Papadopoulou Dionysia, Padua Luca, Carrozzi Maria Chiara. Upper Limb Robotic Rehabilitation After Stroke: A Multicenter, Randomized Clinical Trial.[J]. Journal of neurologic physical therapy : JNPT, 2020, 44(1):537-542.
[6] Chevalier Robert B, Dwyer Jason R. An Open Source, Iterative Dual-Tree Wavelet Background Subtraction Method Extended from Automated Diffraction Pattern Analysis to Optical Spectroscopy.[J]. Applied spectroscopy, 2019, 73(12):621-626.
[7] Kharazian Isfahani Mohsen, Zekri Maryam, Marateb Hamid Reza, Mañanas Miguel Angel. Fuzzy jump wavelet neural network based on rule induction for dynamic nonlinear system identification with real data applications.[J]. PloS one, 2019, 14(12):327-332.
[8] Ahmed R. Adly, Shady H.E. Abdel Aleem, Mahmoud A. Elsadd, Ziad M. Ali. Wavelet packet transform applied to a series-compensated line: A novel scheme for fault identification [J]. Measurement, 2020, 15(1): 269-274.

[9] Jibin Wang, Ping Wang, Suping Wang. Automated detection of atrial fibrillation in ECG signals based on wavelet packet transform and correlation function of random process [J]. Biomedical Signal Processing and Control, 2020, 55(11): 472-477.

[10] Wang Hang, Peng Min-Jun, Wesley Hines J, Zheng Gang-Yang, Liu Yong-Kuo, Upadhyaya Belle R. A hybrid fault diagnosis methodology with support vector machine and improved particle swarm optimization for nuclear power plants [J]. ISA transactions, 2019, 9(5): 726-732.

[11] Dai Xi-Jian, Xu Qiang, Hu Jianping, Zhang QiRui, Xu Yin, Zhang Zhiqiang, Lu Guangming. BECTS Substate Classification by Granger Causality Density Based Support Vector Machine Model [J]. Frontiers in neurology, 2019, 10(6): 489-496.

[12] Qiugang Lu, Michael G. Forbes, Philip D. Loewen, Johan U. Backström, Guy A. Dumont, R. Bhushan Gopaluni. Support vector machine approach for model-plant mismatch detection [J]. Computers and Chemical Engineering, 2020, 133(2): 235-240.

[13] Bahn Emanuel, Alber Markus. On the limitations of the area under the ROC curve for NTCP modelling [J]. Radiotherapy and oncology: journal of the European Society for Therapeutic Radiology and Oncology, 2019, 144(5): 482-487.

[14] Luma Omar, Ioannis Ivrissimtzis. Using theoretical ROC curves for analysing machine learning binary classifiers [J]. Pattern Recognition Letters, 2019, 128(6): 382-387.

[15] Boshen Wan. Applying ROC curve optimization pattern classification algorithm [J]. Progress in natural sciences, 2006(11): 1511-1516.

[16] Yunsheng Wang. Application of ROC curve analysis in evaluating invasive species distribution models [J]. Biodiversity, 2007(04): 365-372.