

## *Retraction*

# **Retracted: Effect Measurement for Human Motion Rehabilitation Training Using Improved Deep Reinforcement Learning and IoT Networks**

### **Security and Communication Networks**

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### **References**

- [1] L. Zhu and L. Liu, "Effect Measurement for Human Motion Rehabilitation Training Using Improved Deep Reinforcement Learning and IoT Networks," *Security and Communication Networks*, vol. 2022, Article ID 3548675, 9 pages, 2022.

## Research Article

# Effect Measurement for Human Motion Rehabilitation Training Using Improved Deep Reinforcement Learning and IoT Networks

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Measuring the effect of human motion rehabilitation training is important to help persons develop motion rehabilitation training plans. The current human motion rehabilitation training effect measurement algorithm has the problems of too large gap between the smoothness of the motion speed curve and the reality, high key frame extraction error rate, low measurement accuracy, long measurement time, and low satisfaction. Therefore, this paper proposes a human motion rehabilitation training effect measurement algorithm using improved deep reinforcement learning and Internet of Things (IoT) networks using IoT network technology to collect human motion rehabilitation training videos. The key frames of the human motion rehabilitation video data are extracted according to the interframe distance, and the metalearning method is used to improve the deep reinforcement learning network, and the obtained key frames are input into the improved deep reinforcement learning network to obtain the motion speed curve of human motion rehabilitation training. The smoothness of the motion velocity curve is calculated, and high smoothness indicates a good human motion rehabilitation training effect, while low smoothness indicates a poor human motion rehabilitation training effect, so as to complete the measure of human motion rehabilitation training effect. The results show that the smoothness of the motion speed curve of the proposed algorithm is closer to reality, the average error rate of key frame extraction is 1.45%, the measurement accuracy of rehabilitation training is more than 90%, the measurement time is controlled below 2.1 s, and the maximum user satisfaction is 93.1, which shows that the practical application of the algorithm is good.

## 1. Introduction

With the continuous improvement of people's living standards, in the process of diagnosis and treatment, people began to pay attention to postoperative rehabilitation reduce patients' postoperative pain and help patients resume motion [1]. The word "rehabilitation" was first proposed in the medical field. According to the World Health Organization, rehabilitation is defined as the comprehensive use of various effective scientific theories, methods, and technical means to promote people with physical and mental disabilities to recover or rebuild their activity ability, self-care ability, professional labor, and other social participation ability to the greatest extent. With the deepening of the research in the field of rehabilitation in recent years, the concept of

rehabilitation has gradually improved and become a special discipline. Different from traditional medicine, modern rehabilitation science is targeted [2]. It has a long-term development prospect of helping patients implement rehabilitation training with an active and positive attitude. It can eliminate and reduce people's dysfunction, make up for and reconstruct people's lacking function, in a bid to improve people's functions in all aspects. In order to obtain better rehabilitation strategies, it is necessary to measure the effect of rehabilitation training, so as to design motion rehabilitation training programs.

Aiming at the important application of measuring the effect of human motion rehabilitation training, literature [3] used machine learning and image segmentation to carry out real-time monitoring algorithm, data sampling and digital

imaging methods to obtain sample images, establish the database about patients' facial expression, and segment the image using machine learning algorithm. On the basis of image segmentation, the detailed information of rehabilitation training was obtained, the rehabilitation training database was established, and the training effect was measured by LASCA technology. The detailed information obtained by this method is not accurate, so it is impossible to obtain high-precision smoothness of motion speed curve. Literature [4] developed measures to evaluate the usability and user value of gait rehabilitation ER. In particular, on the basis of Exowalk, it is verified by different user groups, and statistical analysis is carried out, which can be used as a reference for other gait rehabilitation ER usability and user value design. This method combines the experimental data to measure the training effect of human motion rehabilitation, and takes the overall satisfaction and trust of users as the measurement and evaluation index. However, the method takes a long time and has the problem of low measurement efficiency. In the literature [5], multiple subjects participated in the physical or occupational therapy of a cancer clinic provided by a single institution, completed relevant rehabilitation training, and the obtained data were taken as the experimental data. From the relevant rehabilitation records, the patient and treatment characteristics, fast sprint score, and treatment satisfaction score were extracted. Through the sample  $t$ -test method to evaluate the effect before and after rehabilitation training, the measurement results obtained by this method are inconsistent with the actual results, and the measurement accuracy is low. In literature [6], the white matter integrity of the corticospinal tract, resting state function, and gray matter volume of the primary motor cortex were taken as indicators by collecting relevant physiological parameter data of experimental subjects. The covariance analysis method was used to measure the effect of human motion rehabilitation training, and the user satisfaction of this method was low. Literature [7] studied and compared the effect of including downhill walking training on patients' rehabilitation training. The algorithm takes the physical activity level, exercise tolerance, and muscle function as indicators, constructs the measurement system of the human motion rehabilitation training effect by using analytic hierarchy process, and realizes the measurement of the human motion rehabilitation training effect by combining the weight calculation results. However, this method has the problem of low measurement accuracy, and the practical application effect is not good.

In order to solve the problems existing in the above algorithms, a human motion rehabilitation training effect measurement algorithm based on improved deep reinforcement learning is proposed. The contributions of this paper are as follows: (1) this paper puts forward an algorithm to measure the effect of human motion rehabilitation training based on improved deep reinforcement learning and judges the effect of human motion rehabilitation training through the motion speed curve of human motion rehabilitation training. (2) The key frames of human motion rehabilitation training video data are input into the improved deep reinforcement learning network, and the

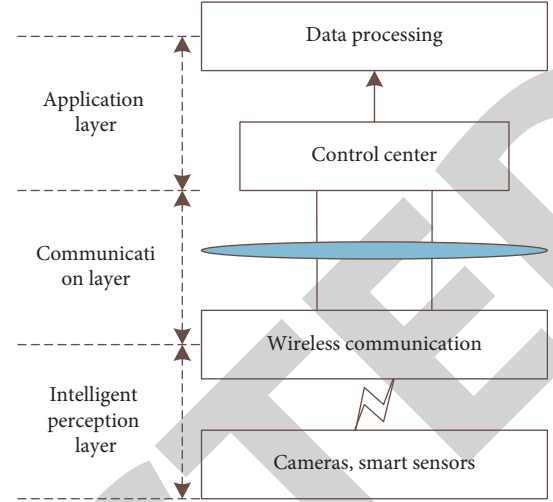


FIGURE 1: Video data acquisition architecture based on IoT networks.

motion speed curve is obtained combined with the network, so as to measure the effect of human rehabilitation training. (3) Using IoT network technology to collect human motion rehabilitation training video has high video data acquisition accuracy and efficiency and can provide high-quality data for subsequent analysis. (4) With multiple data sets as the research basis and through multiple indicators, it is verified that the algorithm in this paper can achieve good application results.

## 2. Methodology

**2.1. Extraction of Key Frames.** The IoT network technology is used to collect human motion rehabilitation training video. The video data acquisition architecture is shown in Figure 1.

The effect measurement algorithm of human motion rehabilitation training based on improved deep reinforcement learning determines the representative gray set of pixels in the dynamic frame [8, 9], calculates the distance between the dynamic frame and each frame in the human motion rehabilitation training video, and obtains the key frame of the video according to the calculation results. The specific steps are as follows:

- (1) Obtaining the current frame and assuming that  $g_n(i, j)$  represents the grayscale value of pixels in the human motion rehabilitation training video, the calculation equation is as follows:

$$g_n(i, j) = 0.3R_n(i, j) + 0.59G_n(i, j) + 0.11B_n(i, j), \quad (1)$$

where  $(i, j)$  represents the pixels in the video;  $R_n(i, j)$  represents the red component of the pixel;  $B_n(i, j)$  represents blue component of the pixel; and  $G_n(i, j)$  represents green component of the pixel.

Using the following equation (1) to modify the value corresponding to the pixel in the gray histogram  $J_n(i, j)$

$$J_n(i, j) = \sum_{m=0}^{M-1} \varepsilon[g_n(i, j) - n], \quad (2)$$

where  $M$  is the number of frames,  $\varepsilon(\cdot)$  represents the impulse function;  $0 \leq n \leq N$ , and  $N$  is the number of color gray levels present in the histogram.

- (2) Detect whether the current frame belongs to the last frame of the lens. If not, proceed to the next step. If yes, set the current frame as the next frame of the lens.
- (3) The dynamic frame  $g_k$  of the shot is obtained.
- (4) Suppose  $F(g_i, g_k)$  is the interframe distance between the dynamic frame and all frames of the lens. It can be calculated by the following equation:

$$F(g_i, g_k) = \sum_{x=0}^{E-1} \sum_{y=0}^{J-1} \min |g_i(x, y) - g_k(x, y)|, \quad (3)$$

where  $g_i$  is the frame  $i$  obtained in the screen and  $J$  and  $E$  are the height and width of the frame.

According to the distance between frames obtained from the calculation above, the distance curve  $F(g_i, g_k)$  is obtained. The key frame of the human motion rehabilitation training video is the frame corresponding to the extreme point in the curve [10, 11], which completes the key frame extraction of the human motion rehabilitation training video.

**2.2. Improved Deep Reinforcement Learning Algorithm Based on Metalearning.** The main process of deep reinforcement learning [12, 13] is that the agent obtains the state  $d_t$  by interacting with the environment at  $t$  time according to the policy  $\omega$ . Select the implementation action  $s_t$  that exists in the action set, based on which obtain the return  $r_t$  and the next status  $d_{t+1}$ . Iterate the above process, stop the iteration at the end of the task, and build the maximization state action value function  $W^\omega(d, s)$  to maximize the cumulative return:

$$W^\omega(d, s) = \max_{\omega} R[r_t + \eta r_{t+1} + \eta^2 r_{t+2} + \dots] \quad (4)$$

$$|d_t = d, s_t = s,$$

where  $R(\cdot)$  refers to the expected function;  $\eta$  refers to the discount factor.

The main purpose of real-time updating and estimating the parameters existing in the network is to evaluate the current state action value function  $W_e = W(d_t, s_t)$ . The parameters existing in the real network are updated by copying the estimated network, and the following real state action value function is constructed:

$$W_t = r + \eta x_{s_{t+1}} W(d_{t+1}, s_{t+1}), \quad (5)$$

where  $d_{t+1}$  refers to the status of the next moment and  $s_{t+1}$  refers to the action of the next moment.

Using the deep reinforcement learning method of the minimum loss function  $Z$ , the parameters in the estimated network can be updated [14] as follows:

$$Z = R(W_t - W_e)^2. \quad (6)$$

Improve the deep reinforcement learning method through metalearning [15, 16] to optimize the above loss function. The specific process is as follows:

- (1) Using  $A$  to refer to the quantity of training tasks, collect samples in the task, and get the test sample  $F_i$  and training sample  $Y_i$ . Aiming at the model parameter  $\vartheta$ , complete the update by the gradient descent method [17, 18] as follows:

$$\vartheta'_i = \vartheta - s \nabla_{\vartheta} Z_{Y_i}(g_{\vartheta}), \quad (7)$$

where  $g_{\vartheta}$  is the model and  $s$  is the learning rate.

- (2) Calculating the loss  $Z_{F_i}(g_{\vartheta'_i})$  of the test sample based on the model parameter  $\vartheta'_i$  and obtaining the cumulative loss  $\sum Z_{F_i}(g_{\vartheta'_i})$  according to the calculation result.
- (3) Obtaining the gradient  $\nabla_{\vartheta} \sum Z_{F_i}(g_{\vartheta'_i})$  based on the model parameter  $\vartheta$ .
- (4) The model parameter  $\vartheta$  was reupdated using the above method to obtain

$$\vartheta = \vartheta - \chi \nabla_{\vartheta} \sum_{Y_i} Z_{F_i}(g_{\vartheta'_i}), \quad (8)$$

where  $\chi$  is the learning rate.

The deep reinforcement learning network is improved by the above process, and the key frames obtained in the above process are input into the improved deep reinforcement learning network to obtain the motion speed curve of human rehabilitation training.

**2.3. Effect Measurement Algorithm for Human Motion Rehabilitation Training.** Input: human motion rehabilitation training sample data.

Output: human motion rehabilitation training effect measurement result.

- (1) Based on the theorem of differential geometry [19], the motion velocity curve  $S$  is described by arc length:  $e = e(s)$ , expand the motion speed curve  $S$  at point  $a_i = e(s_0)$  by the Taylor equation:

$$e(s_0 + \Delta s) - e(s_0) = \alpha \left[ \Delta s + \frac{\Delta s^3 (\phi_1 - \lambda^2)}{6} \right] + \beta \left[ \frac{\lambda \Delta s^3}{2} + \frac{\Delta s^3 (\lambda + \phi_2)}{6} \right], \quad (9)$$

where  $\alpha$  and  $\beta$  are the coordinate system's basis vectors;  $\Delta s$  is the arc length of the local curve;  $\phi_1$  and  $\phi_2$  are tiny quantities;  $\lambda$  is the curve rate.

Approximate equation of adjacent curve at  $e(s_0)$ :

$$\begin{cases} y = \frac{\lambda x^2}{2} \\ y = \lambda x \end{cases}. \quad (10)$$

- (2) Based on the principal component analysis theory [20], the motion speed curve of human rehabilitation is discretized and expressed as  $S = \{a_i\}_{i=1}^m$ , and  $m$  represents the number of discrete points in the speed curve of human rehabilitation.  $a_i(x_i, y_i)$  is used to indicate the point in the motion curve. Take the point  $a_i$  as the center, and use curve discrete points to construct set  $S_i = \{a_i\}_{i-j}^{i+j}$  in neighborhood  $j$ , and suppose  $V$  is the covariance matrix of the set  $S_i$ . The expressions are as follows:

$$V = \begin{bmatrix} v_{11} & v_{12} \\ v_{21} & v_{22} \end{bmatrix}, \quad (11)$$

where the covariance coefficients  $v_{11}$ ,  $v_{12}$ ,  $v_{21}$ , and  $v_{22}$  are calculated as follows:

$$\begin{aligned} v_{11} &= \frac{\sum_{i=1}^m x_i^2 - v_x^2}{m}, \\ v_{12} = v_{21} &= \frac{\sum_{i=1}^m x_i y_i}{m} - v_x v_y, \\ v_{22} &= \frac{\sum_{i=1}^m y_i^2 - v_y^2}{m}, \end{aligned} \quad (12)$$

where  $v_x = \sum_{i=1}^m x_i/m$ ,  $v_y = \sum_{i=1}^m y_i/m$ ,  $m = 2j + 1$ . The eigenvalue of the covariance matrix  $\mu_i$  is obtained on the basis of the following equation (11):

$$\mu_i = \frac{v_{11} + v_{22} \pm \sqrt{(v_{11} - v_{22})^2 + 4v_{12}^2}}{2}. \quad (13)$$

- (3) According to geometry, the bending degree of the curve can be described by curvature, and the change of curvature can measure the smoothness  $P$  of the speed curve of human rehabilitation motion as follows:

$$P = \sum_n^m (l_n - l_{\text{mean}}), \quad (14)$$

where  $l_{\text{mean}}$  is the average value corresponding to the estimated curvature and  $l_n$  represents the estimated curvature of the  $n$  discrete point in the speed curve of human rehabilitation motion.

- (4) The higher the smoothness of the human rehabilitation speed curve, the better the effect of human motion rehabilitation training. Contrary, the lower the smoothness of the human rehabilitation speed curve, the worse the effect of human motion rehabilitation training.

**2.4. Data Set.** The data used for the experiments were obtained from the Mura data set and the collected data set. Mura data set: this data set contains 40895 musculoskeletal X-rays from 14982 cases. Among more than 10000 cases, there were 9067 cases of normal superior musculoskeletal and 5915 cases of abnormal musculoskeletal X-rays of upper limbs, including the shoulder, humerus, elbow, forearm, wrist, palm, and fingers. Each case contains one or more images, which are manually marked by the radiologist. More than 1.7 billion people worldwide have musculoskeletal diseases. Therefore, this study trains this data set, detects bone diseases based on deep learning, automatically locates abnormalities, determines the health status of the body through X-rays of tissues and organs, and then diagnoses the patient's condition, which can help alleviate the fatigue of radiologists. Collected data set: using IoT networks technology to collect human sports rehabilitation training videos. The method of motion photography is used to determine the kinematic data of human lower limbs walking, squatting, and standing on the flat ground and climbing stairs and compare and analyze them. By analyzing and processing the collected image sequence, the kinematics data of human lower limb marker points under different motions are obtained. Integrate the data in the two data sets, taking 30% of the data as test samples and 70% of the data as training samples, so as to improve the authenticity and reliability of the simulation results. The two types of rehabilitation training are shown in Figure 2.

The motion velocity curves for the above two rehabilitation exercises are shown in Figure 3.

**2.5. Experimental Indicators.** In order to verify the effectiveness of the effect measurement algorithm of human motion rehabilitation training based on improved deep reinforcement learning, take the algorithm in the literature [3], the algorithm in the literature [4], the algorithm in the literature [5], the algorithm in the literature [6], and the algorithm in the literature [7] as the comparison algorithm and carry out the following tests.

- (1) Smoothness of the motion speed curve: the closer the smoothness of the motion speed curve obtained by different methods to the smoothness of the actual motion speed curve, the better the measurement effect of human motion rehabilitation training.
- (2) Key frame extraction error rate: this indicator refers to the ratio of the number of key frames extracted by the error to the total number of key frames.

$$E = \frac{y}{c} \times 100\%, \quad (15)$$

where  $y$  refers to the number of key frames extracted by the error and  $c$  refers to the total number of key frames.

- (3) Calculation equation of measurement accuracy is as follows:



FIGURE 2: Human motion rehabilitation training. (a) Rehabilitation training 1. (b) Rehabilitation training 2.

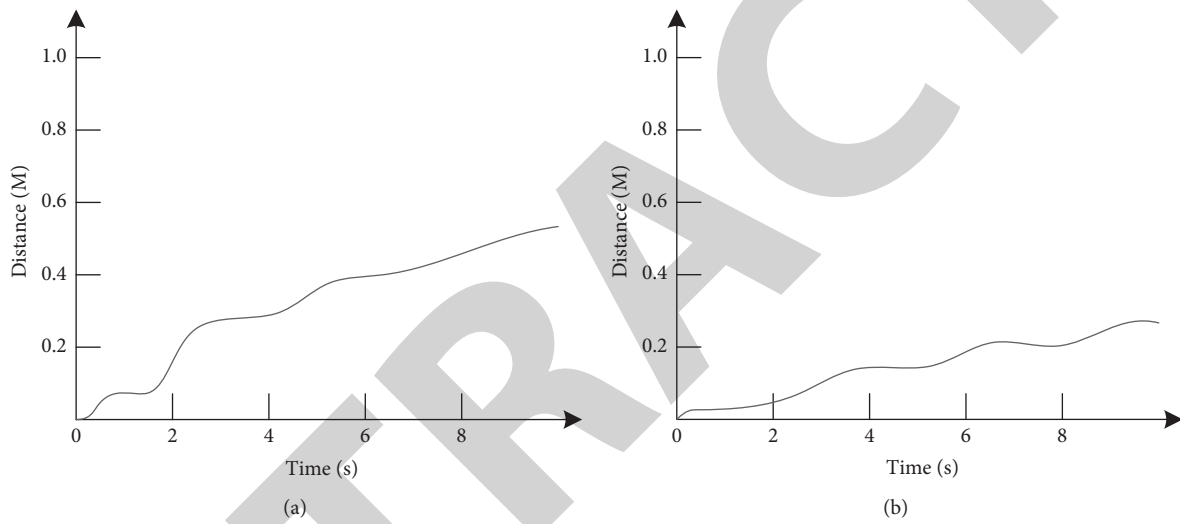


FIGURE 3: Motion speed curve. (a) Rehabilitation training 1. (b) Rehabilitation training 2.

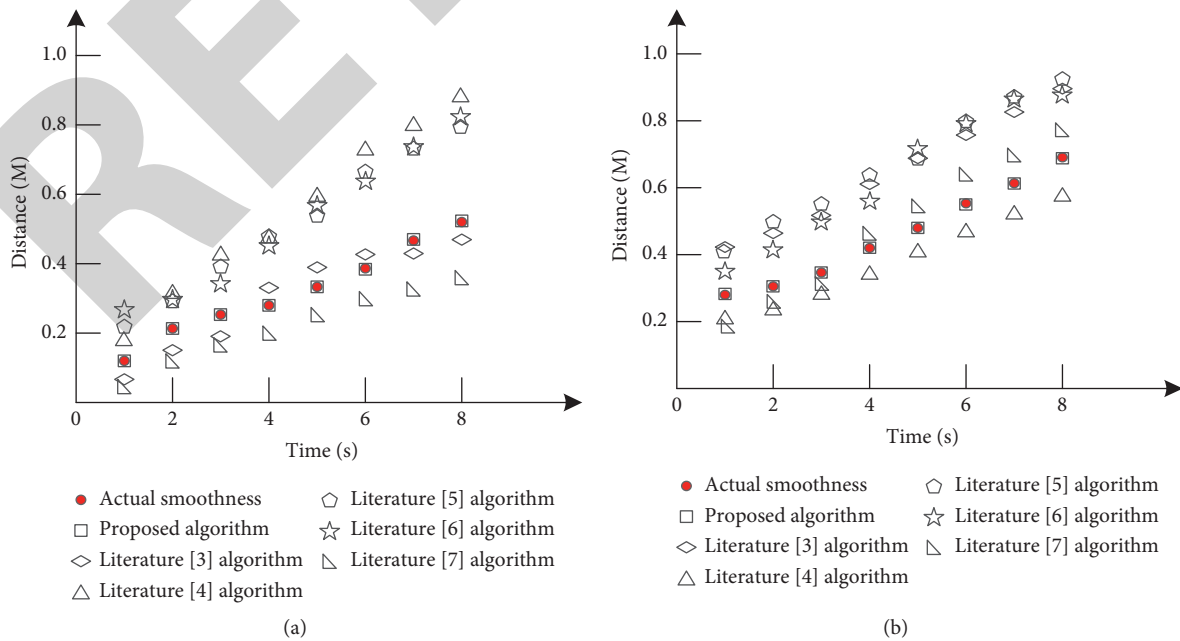


FIGURE 4: Comparison of motion speed curve smoothness. (a) Rehabilitation training 1. (b) Rehabilitation training 2.

TABLE 1: Comparison of the key frame extraction error rate (%).

Number of iterations	Proposed algorithm	Literature [3] algorithm	Literature [4] algorithm	Literature [5] algorithm	Literature [6] algorithm	Literature [7] algorithm
1	1.25	5.66	10.24	17.62	20.36	23.64
2	1.66	5.89	15.61	8.61	24.55	18.99
3	1.36	7.91	12.83	15.14	15.63	18.47
4	1.54	8.62	15.97	16.55	17.18	15.99
Average value	1.45	7.02	13.66	14.48	19.43	19.27

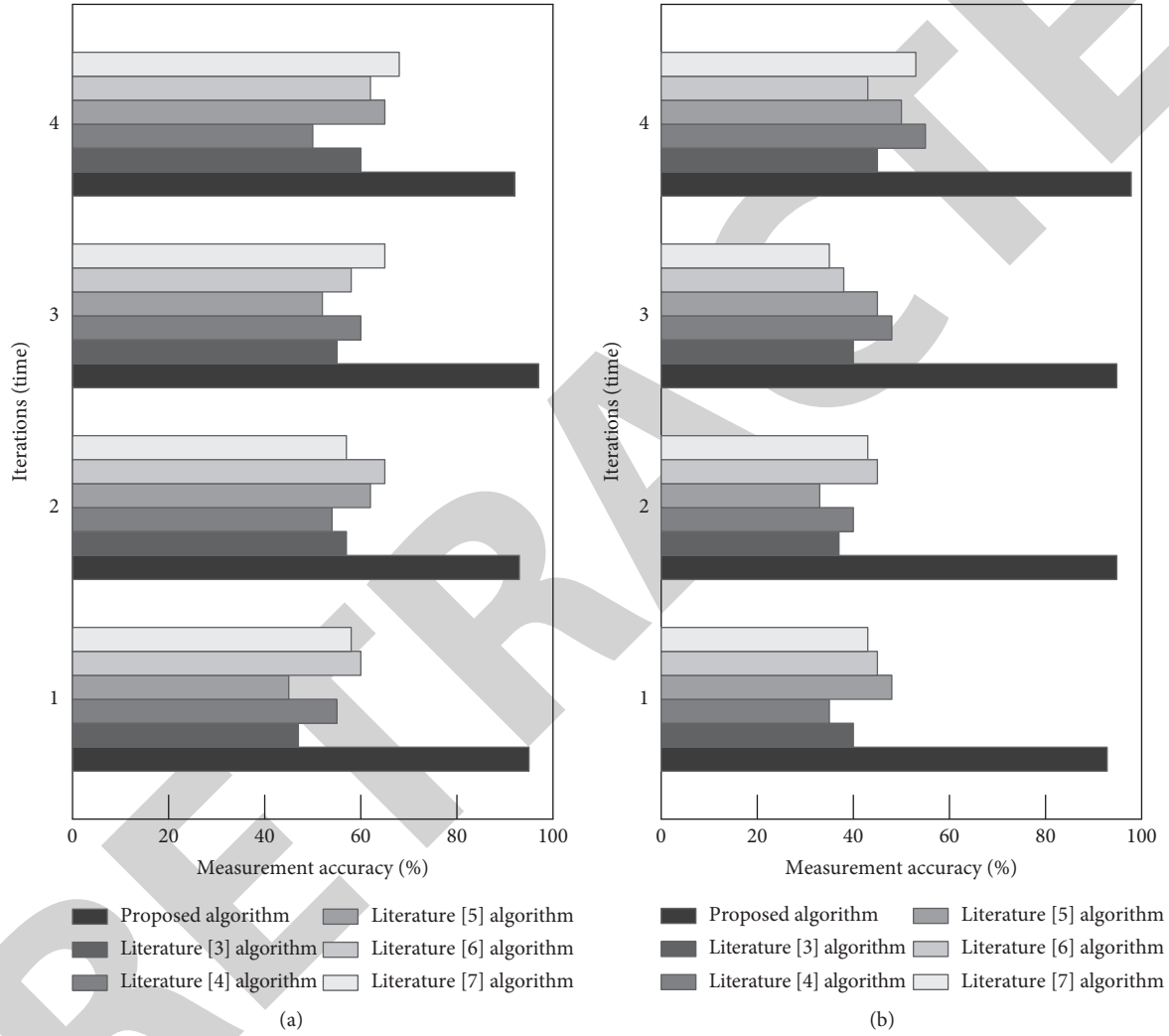


FIGURE 5: Comparison of different algorithms' measurement accuracy. (a) Rehabilitation training 1. (b) Rehabilitation training 2.

$$a = \frac{v_i}{v_j} \times 100\%, \quad (16)$$

where  $v_i$  refers to the amount of data correctly measured for the effect of human motion rehabilitation training and  $v_j$  refers to the total experiment data.

- (4) Measurement time: this indicator refers to the total amount of time consumed from the beginning of measurement to the result of measurement

$$T = |t_i - t_j|, \quad (17)$$

where  $t_i$  refers to the end time of the measurement algorithm and  $t_j$  refers to the start time of the measurement algorithm.

- (5) Satisfaction: multiple users score the satisfaction of the algorithm in this paper, and the value range of scoring results is [0100].

### 3. Results and Discussion

The smoothness of the above two rehabilitation training motion curves is obtained by using the extracted algorithm, the algorithm in the literature [3], the algorithm in the

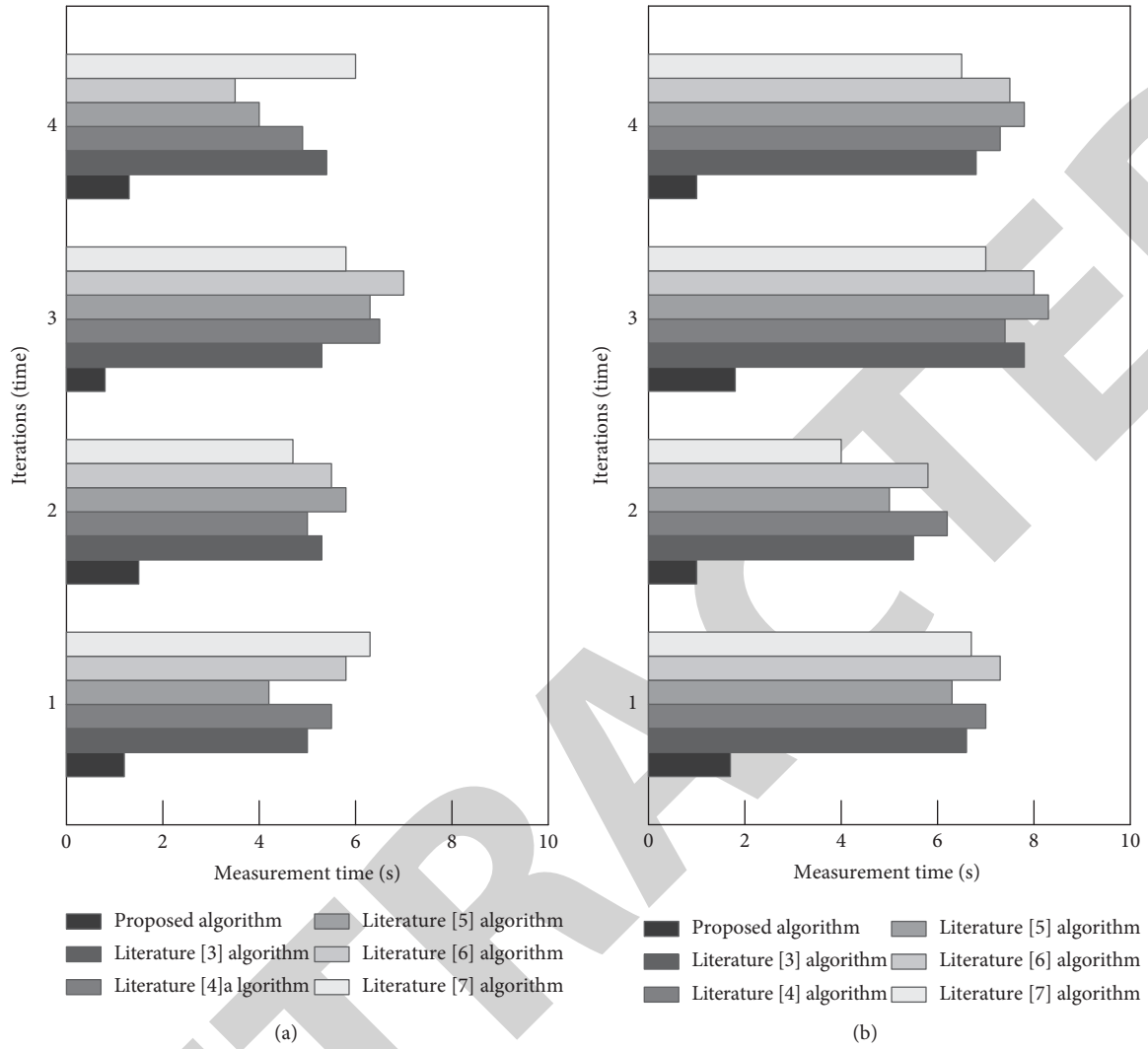


FIGURE 6: Comparison of different algorithms' measurement time. (a) Rehabilitation training 1. (b) Rehabilitation training 2.

literature [4], the algorithm in the literature [5], the algorithm in the literature [6], and the algorithm in the literature [7] and compared with the actual results as shown in Figure 4.

According to the data in Figure 4, in human motion rehabilitation training, the smoothness of the motion speed curve obtained by the proposed algorithm is consistent with the smoothness of the actual curve. There is an error between the smoothness of the motion curve obtained by the methods in the literature [3], literature [4], literature [5], literature [6], and literature [7] and the smoothness of the actual curve. Through the above tests, it can be seen that the proposed algorithm can accurately obtain the smoothness of the motion speed curve and accurately measure the training effect.

In order to further verify the measurement performance of the above algorithm, the key frame extraction error rate is tested as an index. The specific experimental results are shown in Table 1.

Analysis of the data in Table 1 shows that the average key frame extraction error rate of the proposed algorithm is

1.45%, the average key frame extraction error rate of the algorithm in the literature [3] is 7.02%, the average key frame extraction error rate of the algorithm in the literature [4] is 13.66%, the average key frame extraction error rate of the algorithm in the literature [5] is 14.48%, the average key frame extraction error rate of the algorithm in the literature [6] is 19.43%, and the average key frame extraction error rate of the algorithm in the literature [7] is 19.27%, indicating that the proposed method is compared with other methods; the key frame extraction error rate of the proposed algorithm is lower, and the accuracy is higher.

In order to further verify the measurement performance of the above algorithm, the accuracy is tested as an index as shown in Figure 5.

According to Figure 5, when using the algorithm in the literature [3] to measure rehabilitation training 1 and rehabilitation training 2, the accuracy is more than 47% and 40%, respectively, and when using the algorithm in the literature [4] to measure rehabilitation training 1 and rehabilitation training 2, the accuracy is more than 50% and 35%, respectively; When using the algorithm in the literature



TABLE 2: Comparison of satisfaction test results.

User	User satisfaction (%)					
	Proposed algorithm	Literature [3] algorithm	Literature [4] algorithm	Literature [5] algorithm	Literature [6] algorithm	Literature [7] algorithm
User 1	88.6	62.3	59.7	66.4	70.2	71.5
User 2	89.7	63.5	58.8	67.2	70.3	72.6
User 3	90.4	63.7	57.6	65.9	71.4	70.4
User 4	89.5	62.2	56.8	65.3	72.2	69.8
User 5	91.2	62.1	54.9	66.7	71.8	71.4
User 6	87.8	64.0	57.1	65.8	71.3	71.5
User 7	92.3	64.8	57.6	65.4	69.9	69.7
User 8	93.1	64.4	58.3	67.3	73.4	72.1
User 9	88.9	63.9	59.6	67.8	73.5	71.5
User 10	89.5	62.6	59.4	68.0	71.3	71.1
User 11	91.7	63.0	57.4	67.1	72.1	69.8
User 12	93.0	62.6	57.7	66.3	73.2	69.9
User 13	88.7	62.4	56.1	64.7	73.0	72.0
User 14	89.6	63.6	55.0	68.8	72.8	71.4
User 15	91.1	61.7	57.8	68.6	72.4	71.6

[5] to measure rehabilitation training 1 and rehabilitation training 2, the accuracy is more than 44% and 45%, respectively, when using the algorithm in the literature [6] to measure rehabilitation training 1 and rehabilitation training 2, the accuracy is more than 60% and 40%, respectively, and when using the algorithm in the literature [7] to measure rehabilitation training 1 and rehabilitation training 2, the accuracy is more than 58% and 38%, respectively, and when the proposed algorithm is used to measure rehabilitation training 1 and rehabilitation training 2, the accuracy is more than 90% and 93%, respectively, much higher than the measurement accuracy of other algorithms because the proposed algorithm obtains the key frame of human motion rehabilitation training before measurement, so as to obtain the motion speed curve and improve the accuracy of measurement results.

Based on the above test results, the measurement time of the above algorithms is compared as shown in Figure 6.

It is seen from Figure 6 that when using the algorithm in the literature [3], the measurement time is controlled below 8.1 s. When using the algorithm in the literature [4], the measurement time is controlled below 7.2 s. When using the algorithm in the literature [5], the measurement time is controlled below 8.4 s. When using the algorithm in the literature [6], the measurement time is controlled below 8.2 s. When using the algorithm in the literature [7], the measurement time is controlled below 6.9 s, and when using the proposed algorithm, the measurement time is controlled below 2.1 s, indicating that the proposed algorithm has high measurement efficiency.

Fifteen users are selected to measure the effect of human rehabilitation training by using the proposed algorithm, the algorithm in the literature [3], the algorithm in the literature [4], the algorithm in the literature [5], the algorithm in the literature [6], and the algorithm in the literature [7], so as to obtain the satisfaction of users with different algorithms. The test results are shown in Table 2.

Analysis of the data in Table 2 shows that the maximum user satisfaction of the algorithm in the literature [3] is 64.8, the maximum user satisfaction of the algorithm in the

literature [4] is 59.6, the maximum user satisfaction of the algorithm in the literature [5] is 68.8, the maximum user satisfaction of the algorithm in the literature [6] is 73.5, the maximum user satisfaction of the algorithm in the literature [7] is 72.6, and the maximum user satisfaction of the proposed algorithm is 93.1. The algorithm has high user satisfaction, which verifies the effectiveness of the proposed algorithm.

#### 4. Conclusions

When the patient's central nervous system is damaged, there will be symptoms such as the decline of independent living ability and walking ability, which has a serious impact on the patient's physical and mental health. In order to help the patient recover, relevant rehabilitation training is needed. By measuring the patient's rehabilitation effect, it can provide a basis for the equation of later rehabilitation plan. At present, there are some problems in the human motion rehabilitation training effect measurement method, such as the large gap between the smoothness of the motion speed curve and the reality, the high error rate of key frame extraction, the low measurement accuracy, the long measurement time, and low satisfaction. Therefore, this paper proposes an effect measurement algorithm of human motion rehabilitation training based on improved deep reinforcement learning and IoT networks. The proposed algorithm uses IoT network technology to collect the human motion rehabilitation training video. The proposed algorithm improves the deep reinforcement learning network through metalearning to obtain the key frame and completes the measurement of the effect of rehabilitation training by calculating the smoothness of the motion speed curve. The smoothness of the motion speed curve of the proposed algorithm is closer to reality. The average error rate of key frame extraction is 1.45%, the measurement accuracy of rehabilitation training is more than 90%, the measurement time is controlled below 2.1s, and the maximum user satisfaction is 93.1. It shows that the proposed algorithm addresses the problems existing in

the current algorithm and provides relevant basis for patients' human motion rehabilitation. Due to the small amount of experimental data used in the experimental process, the authenticity of the experimental results may be reduced. Therefore, in future work, we need to use more data for experimental testing and improve the method according to the problems existing in the experimental process, so as to further improve the quality of human motion rehabilitation training effect measurement.

## Data Availability

The data used to support the findings of this study are included within the article.

## Conflicts of Interest

The authors declare that there are no conflicts of interest with any financial organizations regarding the material reported in this manuscript.

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