

Retraction

Retracted: The Construction of Adaptive Learning for Sports Based on Aerobics Trajectory Recognition Model

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets 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 own 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] C. Xi, "The Construction of Adaptive Learning for Sports Based on Aerobics Trajectory Recognition Model," *Journal of Function Spaces*, vol. 2022, Article ID 8339745, 8 pages, 2022.

Research Article

The Construction of Adaptive Learning for Sports Based on Aerobics Trajectory Recognition Model

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Perceiving the movement track of aerobics is a key element of learning aerobics, but the current aerobics movement is not very professional, the ability to identify the movement track is weak, and improper movement in the movement process is easy to cause physical injury. In order to improve the safety of athletes in bodybuilding training, this paper uses Kinect to hold the coach's body contour, determine the standard level of coaches' sports, and combine the characteristics for aerobics training, so as to improve the sports level of coaches, through data acquisition, data processing, and feature extraction to assist sports learning, as well as human posture recognition. The calculation and recognition of human skeleton joints are completed by two algorithms, which improve the human motion recognition algorithm. The aerobics data collected by Kinect device is specified and digitized, which enhances the robustness of the system and improves the performance of the algorithm and the accuracy of the motion data.

1. Introduction

The quality of our national physical fitness is gradually becoming a topic that requires attention. And enhancing the national physical fitness will need a certain degree of physical exercise, and the public learning aerobics program movements, the need for repeated practice of the action, and aerobics training will inevitably encounter high costs, risks, and other difficulties, which inspired us to design a set of techniques or equipment that can simplify the daily physical exercise. Perceiving the track of aerobics is the key element of learning aerobics, but the current way of aerobics is not professional, and the recognition of track movement is weak. Improper actions during exercise are easy to cause physical damage. The cost of employing professional aerobics coaches is higher and the audience is smaller. And the judgment of human motion trajectory is not accurate, which affects the actual motion effect. [1].

At present, there are many devices for virtual simulation experiments. These devices can carry out different virtual somatosensory analysis and simulation for human body.

By analyzing the movement state of the human body, the organization recognizes the wearing sports suits of different movements. So athletes can carry out synchronous data tracking in the process of sports [2]. And virtual training will need an animation that can show the characteristics of hot dance to assist training, and 3D animation technology can solve this problem well; it can simulate human movement [3], natural and smooth display of human posture, due to its high accuracy and operability and other characteristics, which is widely used in all aspects of life, including medical detection of human health status game character model design. It is increasingly accepted and used by the general public. The algorithm applied to 3D animation technology is also born and developed rapidly: from the very first frame animation, such as "matchmaker," to the skinning technology which this system focuses on, combining the advantages of both linear skinning algorithm and quaternion linear skinning algorithm [4], removing the dross and taking the essence, better applying to the present day 3D animation technology. The Kinect depth data stream sensor can provide 3D depth data [5]. This paper analyzes the problems

in aerobics training. An innovative aerobics track recognition system based on device motion capture technology is designed, and the corresponding solutions are proposed.

This paper is divided into five structural parts. The first part explains the research background of this system. The research of aerobics track recognition system based on device motion capture technology is analyzed. The second part compares the current research status and references in related fields. The third part introduces the proposed human motion recognition algorithm using Kinect to optimize bone joints. This paper clusters these features based on static k -means algorithm and analyzes the improved hidden Markov model and artificial neural network algorithm, which focus on extracting joint distance features. The fourth chapter tests and analyzes the scheme proposed in this paper. The experiment analyzed 400 different aerobic posture sequences. Finally, this paper is summarized. The aerobics data collected by Kinect device is designated and digitized, which enhances the robustness of the system and improves the performance of the algorithm and the accuracy of sports data.

2. The Related Works

The launch of Microsoft Kinect device has injected fresh blood into the field of artificial intelligence, and with it, the problem of collecting human skeletal joint positions has been solved, and more and more researchers have set out to develop many systems that can be applied to life. Through Kinect recognition of palm bones, for the study of gestural skeletal movements [6–8], through Kinect device accessing, through the design and analysis of a synchronous motion diagnosis and rehabilitation system, some scholars have explored the intelligent home style by developing some learning tools to simplify the lifestyle. Assist athletes in daily medical diagnosis [9]; Xu et al. designed and researched a somatosensory educational game in response to the trend of the times and combined it with contemporary preferences [10]. Mao et al. used Kinect to get a better application in swimming events to guide athletes in stroke contact [11].

The characteristics of the system are as follows. (1) Kinect is a camera used with XBOX360. It is like a camera, which can be connected to the game console through USB interface. (2) Use infrared positioning: Kinect is more intelligent than ordinary cameras. First of all, it can emit infrared rays, so as to carry out stereo positioning of the whole room, and the camera can recognize the movement of the human body with the help of infrared rays. (3) Multiple additional functions: this product can not only recognize the human body through infrared ray but also recognize the complete RGB color and automatically log in for users with the help of face recognition technology. (4) Equipped with its own interface: when Kinect is installed, users must use an independent menu system instead of the original interface of XBOX360. You can also pause the game directly through voice or put your hand in the air and hold the virtual pause button. (5) Built in chat software videokinect.

Many studies have conducted in-depth data collection on some motion data by using human body markers. Through the use of artificial intelligence and retrograde

analysis of movement characteristics under different sports modes, the movement of athletes under video monitoring is disassembled and marked. Recognize the best barrier free movement mode under the condition of human vision. From it, the movement position tracking simulation is carried out to pave the way for future training. Xue et al. solved the problem of body behavior recognition and description, thus making good use of the device to capture the pose and action with inertia and developed the corresponding system [12].

In the choice of human modeling for Kinect, both HMM and ANN algorithms are widely used in the field of modeling due to the ability of HMM algorithm to optimize the computational process using its own dynamic modeling characteristics and ANN algorithm to classify and integrate the modules and resources of the system with its powerful classification capabilities [13]. As a result, techniques as well as devices designed for action recognition using HMM and ANN algorithms are being developed [14]. If the HMM and ANN algorithms are combined to optimize the system model, then the system's ability to collapse, i.e., its stability, is greatly improved and the performance aspect is superior to that of the HMM algorithm alone [15].

The previously mentioned 3D animation technology in the construction of human models needs to take into account the degree of smoothness of limb movements, that is, the coherence of the movement as well as the variability, the system in the calculation not only to consider the trainer's movement data for smooth improvement, but also the robustness of the system, smoothness cannot be discounted, so the requirements of the modeling algorithm is very high. As the difficult problems of the modeling algorithm are not well solved, the development and application of the human model making are limited to some extent. These difficult problems mainly include mannequin modeling techniques, motion data capture, and bone exclusion skinning [16]. Among them, the algorithm of the virtual human modeling technology is not mature enough to achieve the algorithm changes with the action, and the strain is poor, which leads to the trainer to take into account the smoothness of the algorithm but give up the system resources when making the action [17], and the process is slow [18] or can reflect the data changes in real time while ignoring the filtering effect [19], which has a negative impact on the smoothness of the system and the trainer's. Therefore, designing an algorithm that optimizes the human motion detection technique has become a high priority [20].

Inspired by the above idea, this system combines the first estimated static initial center of mass outperform the random center of mass initially estimated using the K -means method [21].

3. Improved Static Aerobics Movement Recognition Algorithm

3.1. Aerobics Movement Recognition Model. Moving target detection and tracking is one of the core topics of computer vision. It integrates the research results of image processing, pattern recognition, artificial intelligence, automatic control,

and other related fields. For different monitoring scenes, the moving target detection and tracking algorithms are also different. This paper mainly studies the detection of moving objects in static scenes and constructs an aerobics action recognition model. The motion node monitoring and identification diagram is described in Figure 1. This system mainly analyzes human joints through different aerobic exercises.

In this paper, the static mean value is collected by using the analysis results of moving nodes of different bones and joints. Using the recognition and analysis of three-dimensional key points, the distance feature is controlled in the psychological degree. Feature extraction is carried out through the initial state of different positions. Estimation of K centers of mass the performance of human aerobics gesture selection and are always random centers of mass for K centers of mass. The category labeling of each aerobics stance is determined by using ANN. Finally, aerobics moves are identified aerobics moves gestures using HMM. The first is to train each movement. Let us assume that the first movement is trained first. Secondly, we cluster 64 groups of data of each same action together. For discrete measurements, that is, the measurements can be exhaustive. At this time, the emission probability is matrix, but for continuous measurements, it is generally GMM model. At this time, the emission probability is generally the value of Gaussian model parameters. These data can be used for action recognition based on gmm-hmm.

The human aerobics posture in each frame is represented by the position of 20 skeletal joints:

$$H_t = \{p_t^1, p_t^2, \dots, p_t^{20}\}. \quad (1)$$

The transformed joint coordinates are as follows.

$$p_t^{ki} = p_t^i - p_t^{\text{hipcenter}}, \quad 1 \leq i \leq N. \quad (2)$$

The feature vector f for each skeleton frame of the aerobics gesture sequence is defined as follows:

$$\begin{aligned} f &= \{p_t^{k1}, p_t^{k2}, \dots, p_t^{kN}\}, \\ F &= \{f_1, f_2, \dots, f_m\}. \end{aligned} \quad (3)$$

The aerobics gesture selection module by using subframe representations of gestures instead of using all similar aerobics gestures. The aerobics gesture similarity is reduced using a well-known K -means-based clustering algorithm with a squared Euclidean distance metric for aerobics gesture selection techniques.

The conventional (nonstatic) K -means algorithm obtains randomized center of masses in the initial step standalone each time, and these centers of masses are sometimes different. Using these cluster identifiers, all actions can be correctly classified.

After reducing the repetitions of the aerobics gesture sequences using each aerobics gesture separately, the common aerobics action figure is shown in Figure 2.

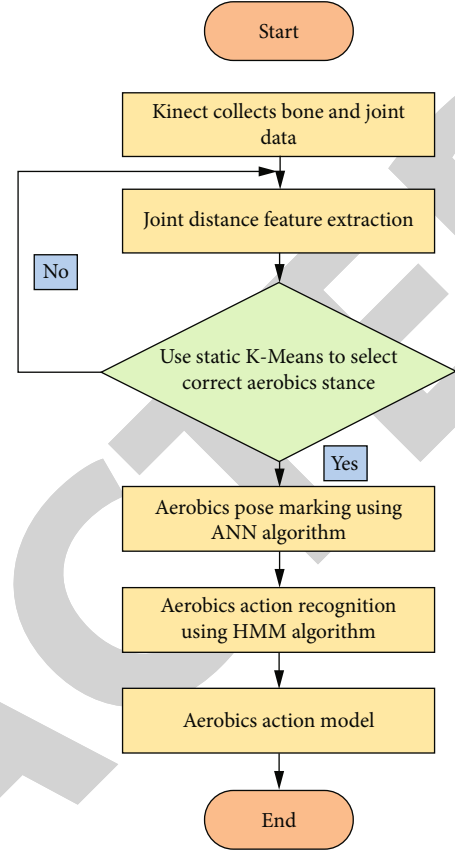


FIGURE 1: Flowchart of aerobics movement recognition system.

In this paper, different neural discrimination of joint points is used for locking. Through the three-dimensional analysis of bones, gesture analysis feature extraction of position matching pattern is carried out. Because the hidden layer of each key node needs and retrograde intelligent matching analysis, it still needs to be further deepened.

The Markov model can correctly identify many instances of aerobics gesture sequences, which are instances of aerobics gestures by using labeled artificial neural networks. Dynamic gesture recognition based on the hidden Markov model is generally based on the temporal characteristics of gestures. A single gesture can be considered as a sequence of different hand shapes, and multiple gestures can be distinguished by hand shapes and their motion trajectories.

$$\lambda = (\pi, A, B),$$

$$\pi_i = P[S_i = q_t], \quad 1 \leq i, t \leq N,$$

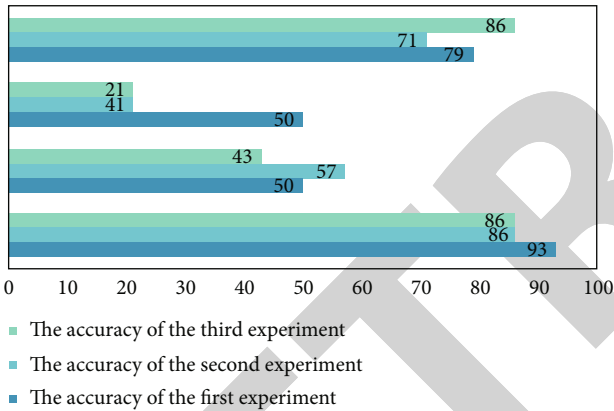
$$a_{ij} = P[S_j = q_{t+1} | S_i = q_t], \quad 1 \leq i, j, t \leq N, \quad (4)$$

$$b_j(k) = P[u_k \text{ at } t | S_j = q_t], \quad 1 \leq j, t \leq N, 1 \leq k \leq R.$$

3.2. Design of Aerobics Track Recognition Method. For the traditional aerobics action recognition, it is necessary to decompose the aerobics action into multiple static actions in advance, because the data computation complexity of multi-image action sequences is high and difficult to implement, so the features of skeletal data are extracted by Kinect



FIGURE 2: Common aerobics movement diagram.

FIGURE 3: Identification process accuracy (%) for the nonstationary K -means training set.

capture, and about 30 frames per second are collected to represent the coherence of aerobics action with continuous human skeletal frame data [22]. The continuous aerobics gesture sequence over a period of time is preset here to represent the change of aerobics. For an aerobics gesture sequence M , G_i denotes the distance feature corresponding to the i -th frame of the aerobics gesture sequence, i.e., the feature quantity, which is N in total, so G_i is the set of distance features extracted from the skeletal data of a human body while performing aerobics gestures.

$$M = (G_1, G_2, \dots, G_i, \dots, G_n). \quad (5)$$

To compare whether two sets of body movements belong to the same aerobics action, which needs to be judged by waveform similarity, and the dynamic time regularization method can stretch the aerobics action sequences of different lengths of the same aerobics action in the time axis accord-

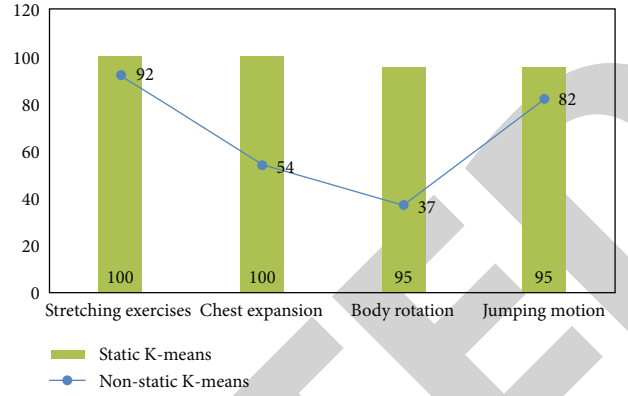


FIGURE 4: Comparison of the UTKinect dataset training set (%).

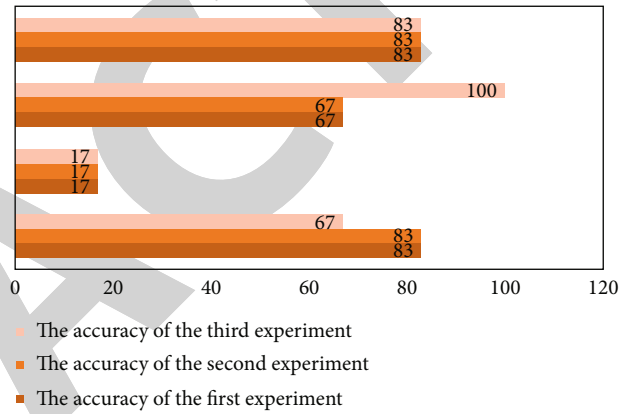
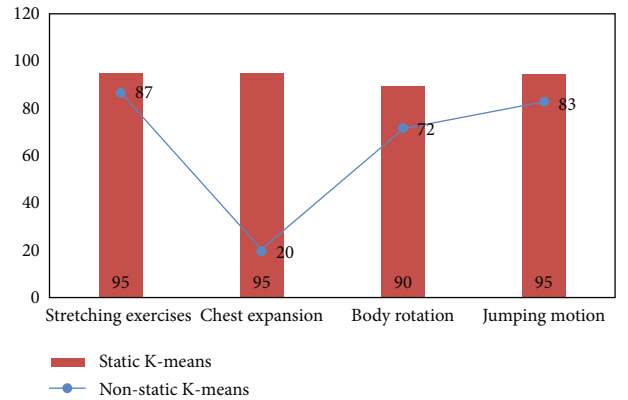
FIGURE 5: Accuracy (%) of the test set identification process using nonstationary K -means.

FIGURE 6: Mean performance of different datasets on the test set.

ingly, so the two aerobics action sequences are of the same length. This means that the two sequences are similar. However, for the processing of time series, the two aerobic movements comparing the length of time series may not be equal, even though the similarity of two aerobic movements is high and the lengths of the sequences are equal, the values of the aerobic movement features at the same time points may be deviated. To solve the above problem, the dynamic time planning idea of DTW algorithm is introduced here to reduce the gap between the action sequences by finding the

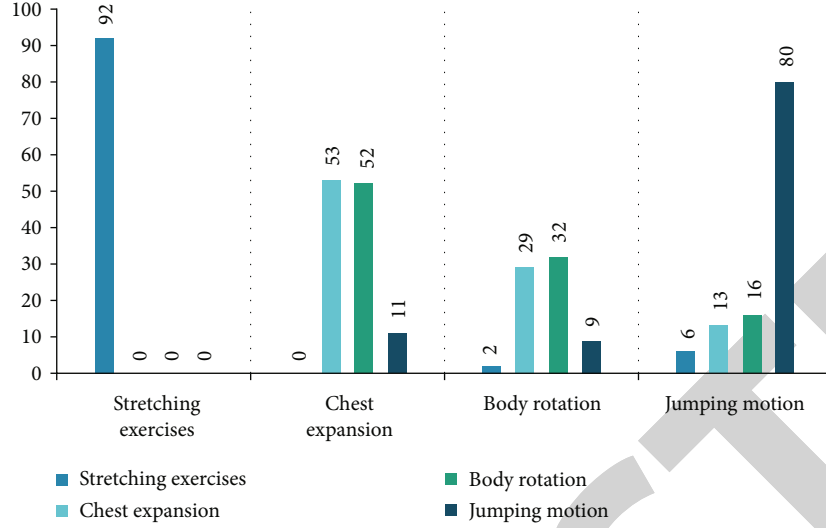


FIGURE 7: Confusion matrix training analysis results.

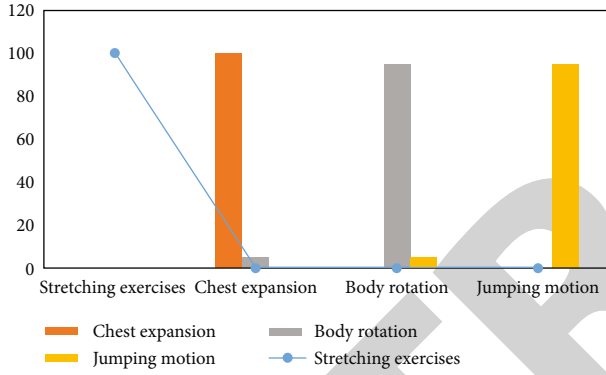


FIGURE 8: Matrix mean analysis of UTKinect dataset.

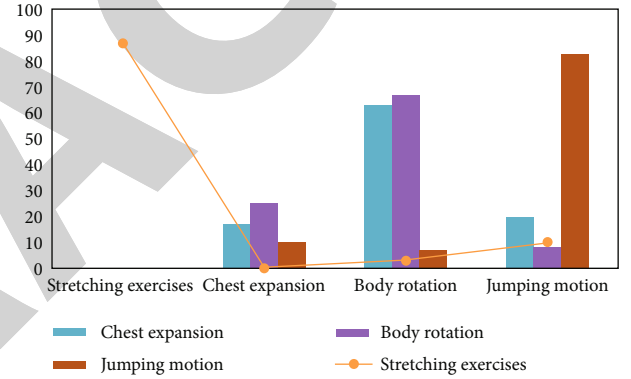


FIGURE 9: Nonstationary K-means confusion matrix.

point-to-point mapping relationship between the two aerobics action sequences, i.e., the matching path with the smallest distance.

The method of extracting motion feature vectors itself may have the problem of time series time point alignment, and DTW can solve this problem very well. The principle of dynamic time regularization is mainly to solve for the minimum distance between two sequences. Suppose T and S are the reference and test aerobics sequences, respectively, and there are two motion sequences of lengths n and m , respectively.

$$\begin{aligned} T &= (T_1, T_2, \dots, T_n), \\ S &= (S_1, S_2, \dots, S_m). \end{aligned} \quad (6)$$

Each sequence contains n and m with different aerobics postures, and their values are the feature vectors of one frame at a time.

However, because linear scaling ignores the possibility that the sequence may be extended or shortened due to the overload of different phases, the recognition efficiency is affected. In order to overcome this effect, this paper proposes

a new dynamic scaling technology. If there are sequences with unequal and, align the two aerobic sequences by linear scaling, shortening the longer sequence or lengthening the shorter sequence. When each sequence contains an equal sum, the minimum distance between the two sequences is obtained by numerically summing the eigenvectors of the corresponding poses of the two aerobic sequences.

In this paper, we construct a matrix grid matrix i and j is expressed as similarity by $d(T_i, S_j)$, and the distance and similarity are inversely proportional.

$$d(T_i, S_j) = \sqrt{\sum_{\omega=1}^N (T_{i\omega} - S_{j\omega})^2}, \quad 1 \leq \omega \leq N, N = 24. \quad (7)$$

Equation (7) represents the Euclidean distance formula for the corresponding points of two different aerobics posture sequences at a 24-dimensional posture feature vector at a point in time, where N denotes the dimension of the distance feature of the aerobic gesture and $T_{i\omega}$ and $S_{j\omega}$ denote the distance feature values corresponding to frame i and frame j of the sequences of different aerobic gestures T and aerobic gestures S . The matrix grid coordinates of (i, j)

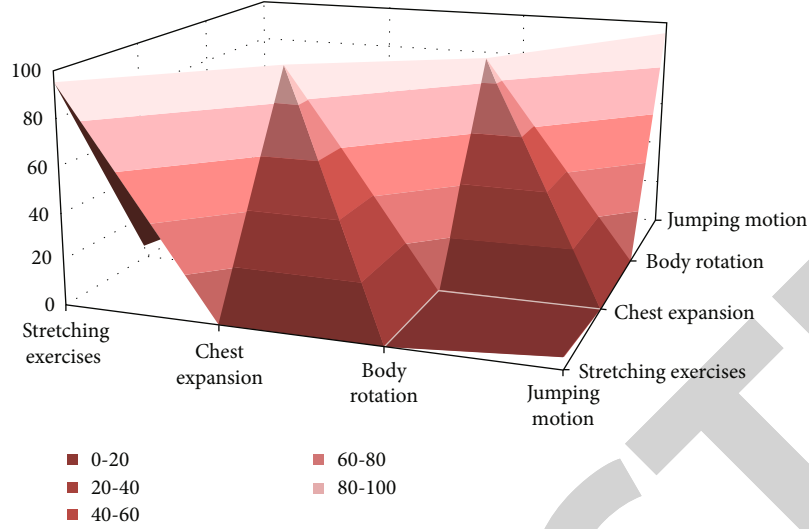


FIGURE 10: Confusion matrix for the UTKinect dataset test set.

represent the correspondence between the points of the aerobic gesture sequence T_i and S_j .

The line through which each point of two different aerobics sequences are aligned is called the planning path, and this line is the optimal $(1, 1)$ to the point (n, m) . This algorithm is called the regularized path algorithm. Equation (8) defines the mapping relationship between different aerobics sequences T and S , where W represents the planning path and k represents the k point in the planning path

$$W = \{w_1, w_2, \dots, w_k, \dots, w_K\} \quad \max(m, n) \leq K < m + n - 1. \quad (8)$$

There are three selection conditions for the planning path, namely, boundary constraint, continuity constraint, and monotonicity constraint:

Boundary constraint: the regularization of two different aerobics posture sequences is always at the two endpoints. To facilitate the study of the skeletal data of aerobic movements, the starting point of the path is $w_1(1, 1)$, the ending point is $w_K(m, n)$, the length of the aerobic movement sequence is set to 30 frames every second, the duration of the aerobic movement is set to 2 seconds, and the output rate of the human skeletal data frames is 30 fps.

Continuity constraint: in order to ensure that the planning path covers each point in the aerobic gesture sequence T and S , the adjacent frames are aligned; assuming that there is a point $w_{k-1}(a', b')$ in the path, the next point a in $w_k(a, b)$ needs to satisfy $a - a' \leq 1$ and b needs to satisfy $b - b' \leq 1$.

Monotonicity constraint: suppose there is a point $w_{k-1}(a', b')$ in the path, the next point $w_k(a, b)$ in a needs to satisfy $a - a' \leq 0$ and b needs to satisfy $b - b' \leq 0$. So the frames in the regularized path are monotonic at the point in time.

After three selection constraints, the point (i, j) can be passed in only three directions, $(i + 1, j)$, $(i, j + 1)$, and $(i + 1, j + 1)$.

Set $Y(i, j)$ as the sum of the Euclidean distances of the points T_i and S_j . The distances of the nearest elements that can reach the point, which is called the cumulative distance. Under the constraint of the selection condition, we find the path that satisfies the condition from the starting point $(1, 1)$ to the end point (n, m) , which is the optimal path to find the point with the minimum cumulative distance corresponding to two different aerobics sequences. The cumulative distance formula is

$$Y(i, j) = d(T_i, S_j) + \min \{Y(i-1, j-1), Y(i-1, j), Y(i, j-1)\}. \quad (9)$$

In order to calculate the similarity of two aerobic gesture sequences, a dynamic time regularization algorithm is used to match them, and the similarity is obtained by inputting the aerobic gesture sequence to be tested and comparing it with the gesture sequence in the standard template. Set the set of action sequences $M = \{S_1, S_2, \dots, S_i, \dots, S_M\}$, and solve the class label(T) of the test aerobic action sequences T by the formula

$$\text{label}(T) = \text{label}(S_c), \quad c = \text{argmin}_i \gamma(T, S_i), \quad i = 1, 2, \dots, M, \quad (10)$$

where i and c are the serial numbers of the action sequence of i in the template database and the sample with the smallest distance in the template database, $\gamma(T, S_i)$ indicates the similarity between T and the action sequence of i , and $\text{label}(S_c)$ is the class of the action sequence corresponding to c .

In τ the process of testing the sample by the above method, the sample to be tested may not be entered into the template database beforehand. To avoid this error, we set a threshold value τ , which represents the similarity of two aerobic sequences, and mark the aerobic sequences outside the template database as nonidentified objects:

$$\tau = \max dtw(S_i, S_j), \quad i = 1, 2, \dots, M, j = 1, 2, \dots, M, i \neq j. \quad (11)$$

4. Analysis of Simulation Results

The experiment was evaluated on 400 different sequences of aerobic gestures (4 movements, 10 objects, different sequences of aerobic gestures) (4 movements, 3 objects, 2 instances, and 5 classes).

First, the experiments are using nonstationary. Based on this method, the training set will be tested and the process will be repeated three times. The average accuracy is shown in Figure 3.

After analysis, the accuracy of all proposed walking actions is high. Each of these measures has high limitations. After the first formal analysis and static simulation, the accuracy of the action studied is high. After the definition analysis, the formal centroid analysis shows a high value. Figure 4 compares and analyzes all training sets. The analysis of different results shows that the method in this paper is higher than other methods in the past.

In this paper, the mean experimental set analysis under different states is carried out. Through the simulation of different action results, it shows that the action accuracy of doing and standing is very high. The significance is strong. Because the analysis repetition of this action is large, the value of stable analysis is high. The accuracy is shown in Figure 5.

The results of the test set show that the nonlinear relationship of the experiment shows good results. The action recognition nodes of each joint are very accurate. Through the static set simulation experiment analysis of the adopted method, the static performance in the mean state is displayed. Figures 6–9 show this process well.

The recognition rates for the case where the training set has a nonstatic K -means confusion matrix are shown in Figure 7.

The recognition rates for the case where the training set has a static K -means confusion matrix are shown in Figure 8.

The recognition rates for the case with a nonstationary K -means confusion matrix on the test set are shown in Figure 9.

The recognition rates on the test set with a static K -means confusion matrix are shown in Figure 10.

From the results of the above simulation comparison experiments, it can be clearly seen that, compared with the nonstatic K -means scheme, the static K -means with static initial centroids has a better effect in correctly identifying the sequence of aerobics motion trajectories.

5. Summary and Outlook

This paper analyzes the problems existing in aerobics training. An aerobics motion trajectory recognition system based on device motion capture technology is designed, and the corresponding solutions are proposed. This scheme improves the performance of traditional human motion rec-

ognition algorithm. Compared with the traditional human motion recognition algorithm, the accuracy of pose selection is improved by using the bone characteristics of Kinect sensor to distinguish motion. Through the simulation and analysis of bone movements in different positions, this paper expounds the posture level of the action model in detail. It not only improves the simulation accuracy of the system but also evaluates it on the public dataset. Compared with the Markov model of neural network, this paper has high reference value. However, the research has certain limitations. In the process of human bone modeling, although the standard data of aerobics items and coach data are compared in real time, each limb movement exceeds a certain range threshold, and the connection of bone joint models will lead to overlapping and unevenness, which is undoubtedly the loss of modeling effect. The next step should focus on the envelope in the process of 3D human modeling. Supporting the envelope will make the action of the model more crash resistant.

Data Availability

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

Conflicts of Interest

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

- [1] G. Jiamin, Z. Qin, C. Hui, and L. Yibin, "Obtaining lower-body Euler angle time series in an accurate way using depth camera relying on Optimized Kinect CNN," *Measurement*, vol. 188, article 110461, 2022.
- [2] Z. Zhuoyu, H. Ronghua, A. Lin et al., "Automated and accurate assessment for postural abnormalities in patients with Parkinson's disease based on Kinect and machine learning," *Journal of Neuroengineering and Rehabilitation*, vol. 18, no. 1, 2021.
- [3] B. Peter, D. B. Anderson, P. Matthew, and W. R. Walsh, "The reliability of the Microsoft Kinect and ambulatory sensor-based motion tracking devices to measure shoulder range-of-motion: a systematic review and meta-analysis," *Sensors*, vol. 21, no. 24, p. 8186, 2021.
- [4] B. Alireza, K. Shunsuke, T. Teppei, and K. Atsushi, "Improved 3D human motion capture using Kinect skeleton and depth sensor," *Journal of Robotics and Mechatronics*, vol. 33, no. 6, pp. 1408–1422, 2021.
- [5] K. JungYup, P. MinJong, K. Sungjun, and S. Dongjun, "Vision-guided six-legged walking of Little Crabster using a Kinect sensor," *Applied Sciences*, vol. 12, no. 4, p. 2140, 2022.
- [6] B. Wang, H. W. Dong, M. M. Zhang, and Z. G. Pan, "Kinect-based dynamic gesture recognition," *Sensors and Microsystems*, vol. 37, no. 2, pp. 143–146, 2018.
- [7] B. Liu, S. Q. Zhou, and X. Zou, "Smart home system based on Kinect motion control," *Science and Technology Innovations*, vol. 3, pp. 84–85, 2019.

- [8] Z. Li-Ying, *Research on Kinect Motion Capture Based Taijiquan Assisted Training System*, Hebei University of Science and Technology, 2016.
- [9] Z. J. Zhao, F. Wang, and F. L. Chang, "A review of research on medical robotics in computer-assisted surgery," *Journal of Shandong University (Engineering Edition)*, vol. 47, no. 3, pp. 69–78, 2017.
- [10] X. Qianqian, *Research on the Design and Development of Embodied Cognition-Based Somatic Educational Games*, East China Normal University, 2019.
- [11] J. Mao, "Research on the application of Kinect somatosensory technology in swimming events," *Journal of Sports Culture*, vol. 6, pp. 100–103, 2016.
- [12] X.-M. Chen, *Motion Evaluation System Based on Human 3D Posture*, Zhejiang University, Hangzhou, 2018.
- [13] C. J. Liu, C. C. Guo, and J. B. Tan, "Lens-free computational imaging techniques based on multi-distance phase restoration," *Infrared and Excitation Engineering*, vol. 47, no. 10, pp. 54–69, 2018.
- [14] N. Wagner, L. H. S. Sundhararajan, and M. Joo, "Research on athlete's action recognition based on acceleration sensor and deep learning," *Journal of Intelligent & Fuzzy Systems*, vol. 40, no. 2, pp. 2229–2240, 2021.
- [15] J. Yang, F. Wang, and J. Yang, "A review of action recognition based on convolutional neural network," *Journal of Physics: Conference Series*, vol. 1827, no. 1, article 012138, 2021.
- [16] G. Kumie, J. Yanli, and Y. Yang, "Arbitrary-view human action recognition via novel-view action generation," *Pattern Recognition*, vol. 118, article 108043, 2021.
- [17] S. Xin, J. Haiyang, and L. Yuanyao, "A novel channel attention mechanism for human action recognition based on convolutional kernel," *Journal of Physics: Conference Series*, vol. 1944, no. 1, article 012015, 2021.
- [18] G. Kourtis, E. Kavakli, and R. Sakellariou, "A rule-based approach founded on description logics for Industry 4.0 smart factories," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 9, pp. 4888–4899, 2019.
- [19] K. Muhammad, A. Ullah, A. S. Imran et al., "Human action recognition using attention based LSTM network with dilated CNN features," *Future Generation Computer Systems*, vol. 125, pp. 820–830, 2021.
- [20] B. Zhuo and H. Wenju, "Human action identification by a quality-guided fusion of multi-model feature," *Future Generation Computer Systems*, vol. 116, pp. 13–21, 2021.
- [21] T. Z. Wint Cho, M. T. Win, and A. Win, "Human action recognition system based on skeleton data," in *2018 IEEE International Conference on Agents (ICA)*, pp. 93–98, Singapore, 2018.
- [22] P. Zhang, C. Lan, J. Xing, W. Zeng, J. Xue, and N. Zheng, "View adaptive neural networks for high performance skeleton-based human action recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 41, no. 8, pp. 1963–1978, 2019.