RECONSTRUCTION OF PHYSICAL DANCE TEACHING CONTENT AND MOVEMENT RECOGNITION BASED ON A MACHINE LEARNING MODEL

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ABSTRACT

With the technological development of movement recognition based on machine learning model algorithms, the content and movements for physical dance teaching are also seeking changes and innovations. In this paper, a set of three-dimensional convolutional neural network recognition algorithms based on a machine learning model is constructed through the collection to recognition of sports dance movement data. By collecting the skeleton information of typical movements of physical dance, a typical movement dataset of physical dance is constructed, which is recognized by the improved 3D convolutional neural network recognition algorithm under the machine learning model, and the method is validated on the public dataset. The experimental results show that the 3D CNNs in this paper can produce relatively satisfactory results for sports dance action recognition with high accuracy of action recognition, which verifies the feasibility of the 3D convolutional neural network action recognition algorithm under the machine learning model for the acquisition to recognition of sports dance actions. It illustrates that the future can be better to open a new direction of physical dance education content through machine learning models in this form.

KEYWORDS

machine learning model; sports dance movements; DDPG algorithm model; 3D convolutional neural network movement recognition algorithm; movement skeleton information dataset

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PAPER INDEX

https://doi.org/10.17993/3ctic.2023.121.267-285

1. INTRODUCTION

With the boom of artificial intelligence, academics have begun to explore the research use of machine learning models in various fields in the hope of reducing human costs and improving output efficiency through these techniques [1-2]. In the era of big data, machine learning models that can model relevant variables with complex relationships will surely become the mainstream of scientific research in the future [3]. Machine learning models are a top science and technology that specializes in how computers can simulate or implement human learning behaviors [4]. Machine learning models are trained to acquire new knowledge or skills and reorganize the existing knowledge structure to continuously improve their performance [5]. With the advent of the third wave of artificial intelligence, machine learning models, which are the core of artificial intelligence, have started to appear frequently in the limelight [6]. Machine learning models are models that make predictions about unknown data based on known data [7]. Machine learning models usually divide the original data set into a training set and a test set. The data are then fitted and optimized several times in the training set to build the model that best reflects the characteristics of the data, and finally, the performance of the model is evaluated in the test set to verify the generalization ability and reliability of the model [8-11].

In recent years, machine learning models have been applied to various fields with remarkable results and their predictive reliability has been widely recognized by researchers. In the literature [12], two sets of classification models were developed to predict students' academic performance at graduation using individual course grades and GPA, respectively. Logistic regression, random forest and plain Bayesian algorithms in machine learning were used to build prediction models for academic performance. The literature [13-14] proposed that when machine learning models were used to predict students' academic performance, the prediction of students' academic performance was more accurate when combining multiple factors compared to a single factor. The literature [15] used machine learning methods to predict changes in major depressive and generalized anxiety disorder symptoms from pre-treatment to 9-month follow-up. The literature [16] revealed the relationship between Internet use behaviors and academic performance and used machine learning models to predict the academic performance of college students with these behavioral data. The literature [17] studied a review of different machine learning algorithms and their application in cardiovascular diseases and found that the application of machine learning can increase the understanding of different types of heart failure and congenital heart disease. The literature [18] proposed a multidimensional approach based on GPS measurements and machine learning to predict injuries in professional soccer. It also provided a simple and practical method to assess and interpret the complex relationship between sports injury risk and training performance in professional soccer. The literature [19] analyzed how to predict and prevent financial losses through public news and historical prices in the Brazilian stock market through a machine learning model. The literature [20] uses Recurrent Neural Networks (RNN) for stock market forecasting. RNN is a machine learning model dedicated to time series, which can take into account past correlation

 https://doi.org/10.17993/3ctic.2023.121.267-285

series when predicting future trends, and the authors introduced the model to the analysis of financial time series and tested it on the Nikkei index, proving the usefulness of the approach. The literature [21] uses oil price movements, gold and silver price movements, and foreign exchange movements as features to demonstrate that the KSE-100 index can be predicted by machine learning algorithms and that the multilayer perceptron outperforms the other algorithms among the machine learning algorithms used. The literature [22] applied machine learning algorithms such as deep learning, random forests, neural networks, and support vector regression machines to stock index prediction in the UK stock market and found that deep learning gave the best prediction results and support vector machines gave the second best results. The literature [23] used the XGBoost algorithm for stock index futures forecasting and compared it with LSTM and traditional autoregressive time series processing methods, and the empirical results showed that the XGBoost algorithm was superior in determining the ups and downs. Research on dance moves also abounds, and the literature [24] proposes a modern deep architecture for C3D that can learn on large-scale datasets. And the C3D method based on linear classifiers outperforms or approaches the current state-of-the-art methods in both recognition accuracy of action videos. The literature [25] uses convolutional neural networks (CNNs) for the classification of Indian classical dance movements. Two hundred dance poses and gestures were collected from online videos and offline recordings, respectively, and the experiments were compared with the results of other classification algorithms on the same dataset, finally obtaining a recognition rate of 93.33%. In [26], six Greek folk dance movements were collected using a Kinect sensor, and four common classifiers were used to directly classify the movements on the raw data to compare the classification results, and the effect of different body joints on the recognition rate was also investigated. The literature [27] studied motion data acquisition devices, among which the Kinect depth vision sensor device has the advantages of high depth map resolution, low cost, and the ability to directly track the human skeleton motion trajectory.

In this paper, the typical movement dataset of sports dance was constructed by collecting the skeleton information of the typical movement of sports dance. This dataset was identified using a 3D convolutional neural network recognition algorithm based on a machine learning model, and the original data recorded in this dataset was checked for missing skeleton point data. In the case that the skeleton point data was lost in the experiment and could not be recorded, the missing skeleton point data of a frame was filled with the skeleton data of the previous frame to reduce the influence of the subsequent machine learning model on the judgment of different movements. The frame rate of the few skeletal sequences of typical sports dance movements obtained is 30 fps. The duration of each movement in the dataset is different, and the corresponding number of frames is also different. The sequence length of each movement sequence in the dataset is unified, and the maximum number of frames of the samples in the dataset is obtained. The remaining movement samples with less than the maximum number of frames are copied to the last frame and supplemented to the maximum number of frames for subsequent input into the machine learning model for training Learning. After the dataset is completed, it is input

https://doi.org/10.17993/3ctic.2023.121.267-285

into the machine learning model, and the 3D convolutional neural network recognition algorithm is used to train the dataset. The experimental results show that the 3D CNNs in this paper have greater recognition advantages and accuracy compared with several other action recognition algorithms, which can help the innovative development of physical dance teaching contents and also make another perspective of physical dance teaching methods. It is verified that the 3D convolutional neural network action recognition algorithm under the machine learning model is feasible in the acquisition to recognition of physical dance actions, which can better open a new direction of physical dance education content through this form of machine learning model and provide an optional path for the reconstruction of physical dance teaching content and action recognition.

2. MACHINE LEARNING MODELS

With the development of information technology, intelligent algorithms represented by reinforcement learning are increasingly used in the field of robot control with their adaptive characteristics. In recent years, DQN algorithms combining deep neural networks and reinforcement learning have been proposed to solve the problem of high-dimensional input to machine learning models. However, DQN is still an algorithm oriented to discrete control and has insufficient capacity to handle continuous actions. In the practical control of machine learning models, the angular output of each joint is a continuous value, and if the range of values taken for each joint angle is discretized, the number of behaviors grows exponentially with the number of degrees of freedom. If this accuracy is further improved, the number of values taken will grow exponentially [28-29].

2.1. THE DDPG ALGORITHM MODEL USED FOR MACHINE LEARNING

DDPG is an Actor-Critic based algorithm in reinforcement learning, the core idea of which is to use the Actor-network to generate the behavior policy of the intelligence, and the Critic network to judge the good and bad actions and guide the updated direction of the actions.

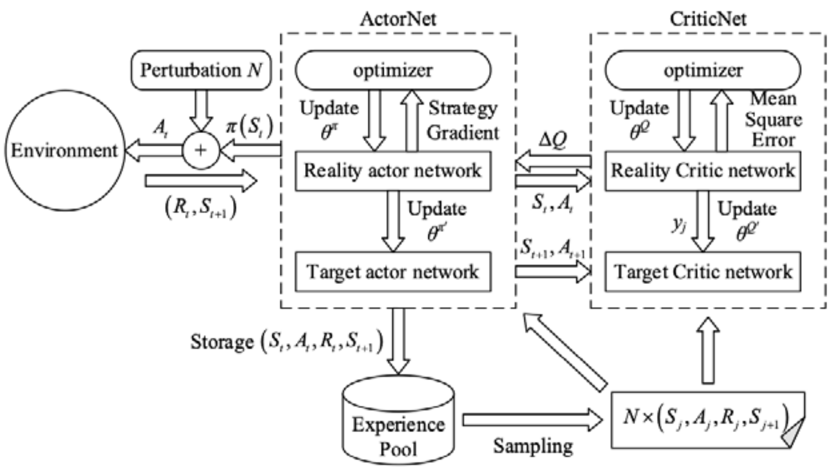

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Figure 1. DDPG algorithm structure

As shown in Figure 1, the DDPG algorithm structure contains an Actor-network with parameters and a Critic network with a parameter to compute the deterministic policy and action-value function, respectively. Since the learning process of a single network is not stable, the Actor-network and the Critic network are subdivided into a realistic network and a target network, respectively, drawing on the successful experience of DQN fixed target networks. The Actor-network and the Critic network are each subdivided into a realistic network and a target network. The real network and the target network have the same structure, and the target network parameters are softly updated by the real network parameters with a certain frequency.

The loss function of the realistic Critic network is:

$$J(\theta^{Q}) = \frac{1}{m}\sum_{j=1}^{m}\omega^{j}(y^{j} - Q(S_t^{j}, A_t^{j}, \theta^{Q}))^{2} \tag{1}$$

Among them:

$$y^{j} \begin{cases} R^{j}, end^{j} \\ R^{j} + \gamma Q(S_{t+1}^{j}, A_{t+1}^{j}, \theta^{Q'}), not\ end^{j} \end{cases} \tag{2}$$

m is the number of samples, ω^{j} is the weight of the different samples used, $Q(S_t^j, A_t^j, \theta^Q)$ is the action value calculated by the realistic Critic network when sample j takes action A_t at the state S_t, y^j is the target action value calculated by the samples and derived from the target Critic network, R^j is the immediate reward obtained by sample j for taking action A_t at the state S_t, and γ is the discount factor.

The loss function of a realistic Actor network is :

$$J(\theta^{\pi}) = \frac{1}{m}\sum_{j=1}^{m} Q(S_t^{j}, A_t^{j}, \theta^{Q}) \tag{3}$$

Which, finding the minimal value of this loss function $J(\theta^{\pi})$ by the gradient descent method is equivalent to the process of maximizing the action value $Q(S_t^j, A_t^j, \theta^Q)$.

The target Critic network and target Actor network parameters are updated in the following way:

$$\theta^{Q'} \leftarrow \tau\theta^{Q} + (1-\tau)\theta^{Q'} \tag{4}$$

$$\theta^{\pi'} \leftarrow \tau\theta^{\pi} + (1-\tau)\theta^{\pi'} \tag{5}$$

τ is the update coefficient, and the range is 0.01~0.1 to avoid excessive parameter changes.

When a machine learning model has a high degree of freedom, an additional class of exploration strategy, maximum a posteriori policy optimization, is needed to enhance the efficiency of the machine learning model based on the use of the DDPG algorithm model. The maximum a posteriori policy optimization approach models the reinforcement learning problem as an inference problem from a probabilistic point of view. Assuming the probability of completing the task, the probability, according to the inference problem, is:

$$\log p_\pi(O=1) = \log \int p_\pi(\tau) p(O=1|\tau) d\tau$$
$$\geq \int q(\tau) \left[\log p(O=1|\tau) + \log \frac{p_\pi(\tau)}{q(\tau)} \right] d\tau \tag{6}$$

Let the loss function :

$$J(q,\pi) = E_q \left[\sum_t r_t / a \right] - KL(q(\tau) \| p_\pi(\tau)) \tag{7}$$

where: $q(\tau)$ is the proposed distribution. the optimization problem can be solved by the EM method, and the optimal proposed distribution $q(\tau)$ is obtained in step E. The non-parametric optimization solution in this step is:

$$q_i(a|s) \propto \pi(a|s,\theta_i) \exp\left(\frac{Q_{\theta_i}(s,a)}{\eta^*}\right) \tag{8}$$

where the optimal temperature term η^* can be optimized according to equation (9):

$$g(\eta) = \eta\varepsilon + \eta \int \mu(s) \log \int \pi(a|s,\theta_i) \exp\left(\frac{Q_{\theta_i}(s,a)}{\eta}\right) da ds \tag{9}$$

In the M-step, the optimal proposal distribution is used to update the neural network strategy:

$$\max_\theta J(q_i,\theta) = \max_\theta E_{\mu_q(S)}[E_{q(a|s)}[\log \pi(a|s,\theta)]] + \log p(\theta) \tag{10}$$

2.2. OBSERVED AND REWARDED VALUES OF MACHINE LEARNING MODEL ALGORITHMS

To give full play to the performance advantages of the DDPG algorithm, this paper takes into account the motion state of the machine learning model, the processing efficiency of the intelligent body, the environment and other factors, and selects some observations as shown in Table 1.

Table 1. Learning process observations

Parameter	Symbol
Machine learning model location	$[x, y, z]$
Machine learning model pose angle	$[roll, pitch, yaw]$
Machine learning model speed	$[v_x, v_y, v_z]$
Contact force	$[F_{N_l}, F_{N_r}]$
Joint torque output	$[t_{hip_l}, t_{hip_r}, t_{knee_l}, t_{knee_r}, t_{tire_l}, t_{tire_l}]$
Last joint moment output	$[t'_{hip_l}, t'_{hip_r}, t'_{knee_l}, t'_{knee_r}, t'_{tire_l}, t'_{tire_l}]$

https://doi.org/10.17993/3ctic.2023.121.267-285

and the following weighted reward values r are designed based on the observed values, where $k1\sim k9$ are the weights.

(1) The speed reward value r_v, which is to encourage the machine learning model to move forward, is shown in equation (11):

$$r_v = k_1 \cdot v_x \tag{11}$$

where: v_x is the velocity of the machine learning model on the x axis.

(2) The stability reward value r_s, lies in rewarding the machine learning model for completing smooth motions in both instantaneous and global decisions, as shown in equation (12):

$$r_s = -(y - y_{init})^2 - k3(z - z_{init})^2 - k_4 roll^2 - k_5 pitch^2 - k_6 yaw^2 \tag{12}$$

where: y, z denotes the current position of the machine learning model on the y, z axis, y_{init}, z_{init} denotes the position of the machine learning model on the y, z axes, $roll, pitch, roolll, pit\ \ yaw$ denote the attitude angle (roll angle, pitch angle, yaw angle) of the machine learning model.

(3) The joint stability bonus value r_3, which lies in improving the energy utilization efficiency of the robot, is shown in equation (13):

$$r_{js} = -k_7 \sum_i (t_i' - t_i)^2 \tag{13}$$

where: t_i and t_i' represent the output of each joint torque and its torque output at the previous time.

(4) The value of touchdown reward r_F, lies in rewarding the machine learning model for controlling the same contact force between its own two feet and the ground, reducing the probability of training to generate singular motion poses, as shown in equation (14):

$$r_F = -k_8 (F_{N_l} - F_{N_r}])^2 \tag{14}$$

where: F_{N_l}, F_{N_r} denotes the contact forces between the left and right feet of the machine learning model and the ground, respectively.

(5) The motion duration reward value r_c, lies in encouraging the machine learning model to keep moving, as shown in equation (15):

$$r_c = k_9 T \tag{15}$$

where T is a constant and takes any value.

2.3. THREE-DIMENSIONAL CONVOLUTIONAL NEURAL NETWORK

Compared with other traditional deep learning methods, 3D convolutional neural networks are not limited to the input of 2D single-frame images, and can better extract features from the temporal and spatial dimensions and extract motion information of

https://doi.org/10.17993/3ctic.2023.121.267-285

multiple consecutive frames after reinforcement learning algorithms by machine learning models.

The three-dimensional deep convolutional neural network used in this paper includes four convolutional layers, two downsampling layers, two fully connected layers and one Softmax classification layer, and the downsampling layer uses Max-pooling with a kernel size of 3×3×3 and a step size of 1, as shown in Figure 2.

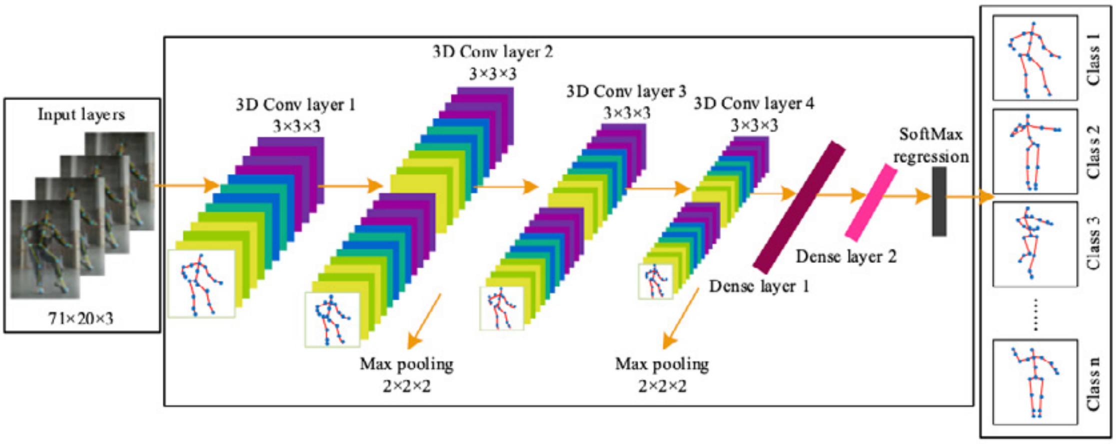

Figure 2. Three-dimensional convolutional neural network framework

To capture the sports dance movement information in multiple consecutive frames, the features are calculated from the spatial and temporal dimensions, the value of the cell with position coordinates (x, y, z) in the jth feature map of the ith layer is given by the following equation:

$$V_{ij}^{xyz} = f\left(b_{ij} + \sum_{r}\sum_{l=0}^{l_i-1}\sum_{m=0}^{m_i-1}\sum_{n=0}^{n_i-1}\omega_{ijr}^{lmn}\, v_{(i-1)r}^{(x+l)(y+m)(z+n)}\right) \tag{16}$$

The time dimension of the 3D convolution kernel is n_i, and the weight value of the convolution kernel connected to the rth feature map at position (l, m, n) is ω_{ijr}^{lmn}.

The ReLU function is the most commonly used activation function in deep machine learning models, which keeps the original feature value unchanged when the input feature value is greater than 0, and sets it to 0 when it is less than 0. This is the unilateral inhibition of the activation function, which allows the model parameters to become sparse and thus reduces the risk of overfitting to some extent. In addition, the derivative of the activation function is very simple to compute, which can speed up the computation to a certain extent, and the derivative is always 1 when the input is positive, so it can effectively alleviate the problem of gradient disappearance, the ReLU activation function is defined as:

$$f(x) = \max(0, x) = \begin{cases} 0, (x \le 0) \\ x, (x > 0) \end{cases} \tag{17}$$

Pooling is also known as downsampling, where, unlike the processing of 2D images, the information of the video in the temporal dimension is taken into account;

by pooling, the feature map is reduced, the dimensionality of the data is reduced, and the number of calculations is reduced, making it easier to train and improve accuracy:

$$V_{x,y,z} = \max_{0 \le i \le s_1, 0 \le j \le s_2, 0 \le k \le s_3} \left(\mu_{x \times s+i, y \times t+j, z \times r+k} \right) \tag{18}$$

The Softmax function is often used in the last layer of a classification task to map an n-dimensional vector x to a probability distribution such that the probability of the correct category tends to 1 and the probability of the other categories tends to 0, and the sum of the probabilities of all categories is 1.

The Dropout strategy is to temporarily discard the neurons in the deep model from the network and disconnect them according to a certain probability when the model is trained so that the closed neurons do not participate in the calculation of forward propagation and the update of weights by the backward gradient. Therefore, Dropout can be considered as an integration method, i.e., averaging different model architectures over several iterations, thus significantly reducing the risk of overfitting.

3. METHODS OF RECONSTRUCTING THE CONTENT AND MOVEMENT IDENTIFICATION OF PHYSICAL DANCE TEACHING

At present, there are many action recognition methods based on deep learning, and the commonly used classical action recognition algorithms are the C3D algorithm, P3D ResNet algorithm, and ConvLSTM algorithm, and these algorithms have a good effect on action recognition. To realize the recognition of physical dance teaching content movements, this paper firstly constructs a physical dance movement dataset, which needs to record the skeleton information of dancers, using the skeleton information for recognition can be processed faster and reduce the storage space. Secondly, based on the machine learning model and 3D convolutional neural network, an improved model is proposed for the recognition of physical dance movements. In this paper, the Dropout technique is also used to reduce the overfitting phenomenon, and Dropout is experimentally compared by setting different ratios.

This experiment uses the 5-fold cross-validation method, in which the pre-processed sports dance typical movement dataset is randomly divided into 5 groups, of which 4 groups are used as the training set and 1 group is used as the test set, and then the results of 5 times are averaged as the recognition rate.

3.1. PHYSICAL DANCE MOVEMENT DATA PRE-PROCESSING

To reduce the impact of the subsequent machine learning model on the judgment of different movements, the missing skeletal data of a certain frame was filled with the skeletal data of the previous frame to check the missing skeletal data of the recorded raw data. To reduce the redundant information, only one frame out of every five frames of the original data was kept, and the maximum number of frames for each action in the dataset is shown in Table 2, The remaining action samples with less than

https://doi.org/10.17993/3ctic.2023.121.267-285

the maximum number of frames are copied to the last frame to be added to the maximum number of frames for subsequent input into the machine learning model for training and learning.

Table 2. Sports Dance Motion Dataset Motion Name and Maximum Number of Frames

Dance type	Serial number	The action name	The maximum number of frames
Modern dance	1	Next to the T-step step	62
	2	Z-step	37
	3	Pendulum	60
	4	Side-click steps	30
	5	Single step	33
Waltz	6	Step back	50
	7	Lift the step	40
	8	One-handed one-handed step	42
	9	Single step	36
Tango	10	Cats wash their faces	25
	11	Alternate cover hands	30
	12	Flick your fingers	35
Latin dance	13	Flat step	48
	14	Drag	31
	15	Shrug	40
	16	Crankulated arms	38
Samba	17	High shake hands	35
	18	Alternate waving hands	32
	19	Wave your hands	50
	20	Draw circles with both hands	24

3.2. EXPERIMENTAL DATA ANALYSIS METHODS

Using the test set in the dataset, the recognition results of each method for 20 typical sports dance movements are evaluated in terms of accuracy. the recognition results of the experiments using the 3D convolutional neural network recognition method under the machine learning model of this paper are calculated, which can clearly express the categories and numbers of correct and incorrect recognition of each movement, and then the recognition accuracy of three different types of recognition methods are calculated, namely, the UTKinect dataset, the MSRAction3D dataset and the TYYDance dataset of this paper under the recognition algorithm. MSRAction3D dataset and the sports dance action TYYDance dataset of this paper are then calculated for the overall dance action recognition accuracy under the recognition algorithm, and finally, the method of this paper is compared with the classical algorithm, and the corresponding recognition results and conclusions are drawn.

4. EXPERIMENTAL RESULTS AND ANALYSIS

First, to alleviate the overfitting phenomenon, the Dropout technique was used, and the Dropout ratios were set to 0.2, 0.4, 0.5, 0.6, and 0.8 and the experiments were conducted on the dataset of this paper, and the results of the validation set are shown in Figure 3. After 50 iterations, the recognition accuracy of the Dropout ratio of 0.5 is slightly higher than that of the ratio of 0.4.

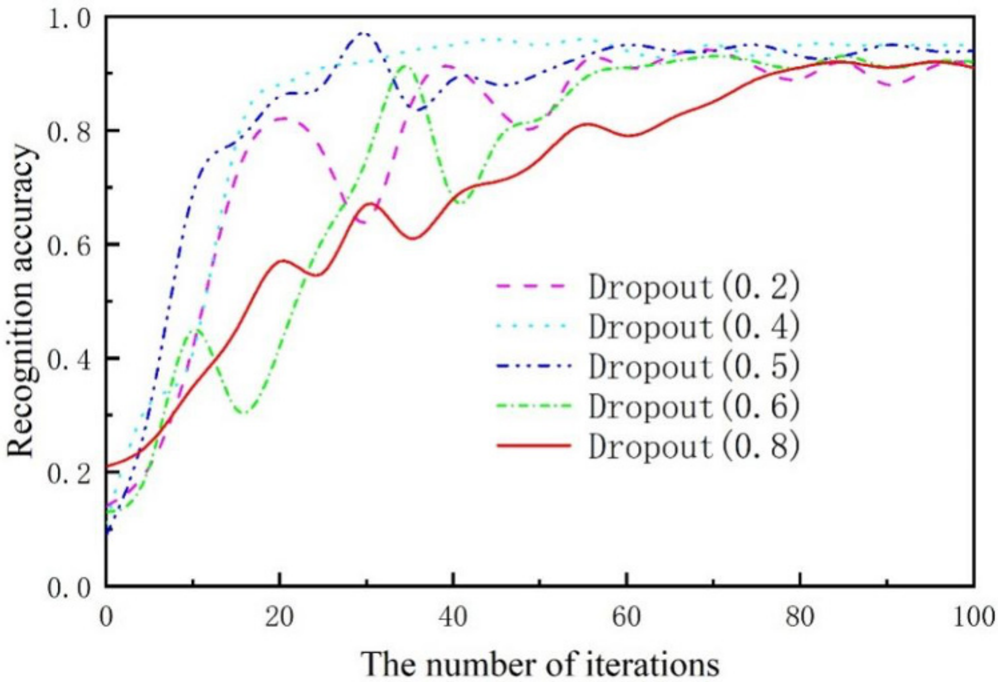

Figure 3. Experimental results of different Dropout ratios

To verify the effectiveness of the 3D convolutional neural network dance movement recognition method based on the machine learning model proposed in the text, experiments were conducted on the public dataset UTKinect dataset, MSRAction3D dataset and the sports dance movement TYYDance dataset of this paper. The UTKinect dataset contains 10 types of movements with 220 movement samples, the MSRAction3D dataset contains 20 types of movements with 540 movement samples, and the dance movement dataset in this paper contains 20 types of dance movements with 640 movement samples, The dance movement dataset in this paper contains 20 types of dance movements, with a total of 640 movement samples.

Figure 4 shows the recognition accuracy of the training set and Figure 5 shows the recognition accuracy of the test set. 82% recognition rate was obtained on the

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UTKinect dataset, 90% recognition rate was obtained on the MSRAciton3D dataset, and 96% recognition rate was obtained on the TYYDance dataset. The reasons for the better recognition results are as follows: (1) in the selection process of the typical movements of sports dance, the dance movements with relatively large differences in movements are selected; (2) more dance movements are collected.) more samples of movements were collected, and more deep learning data were obtained; (3) the collected dance movements had more duration than the general movements, and more movement representations were also obtained.

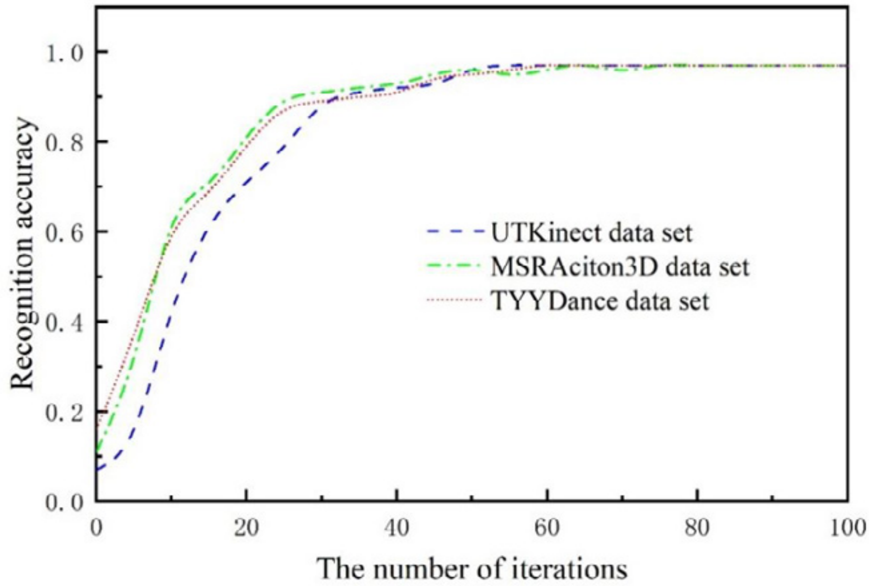

Figure 4. The training recognition rate of three data sets

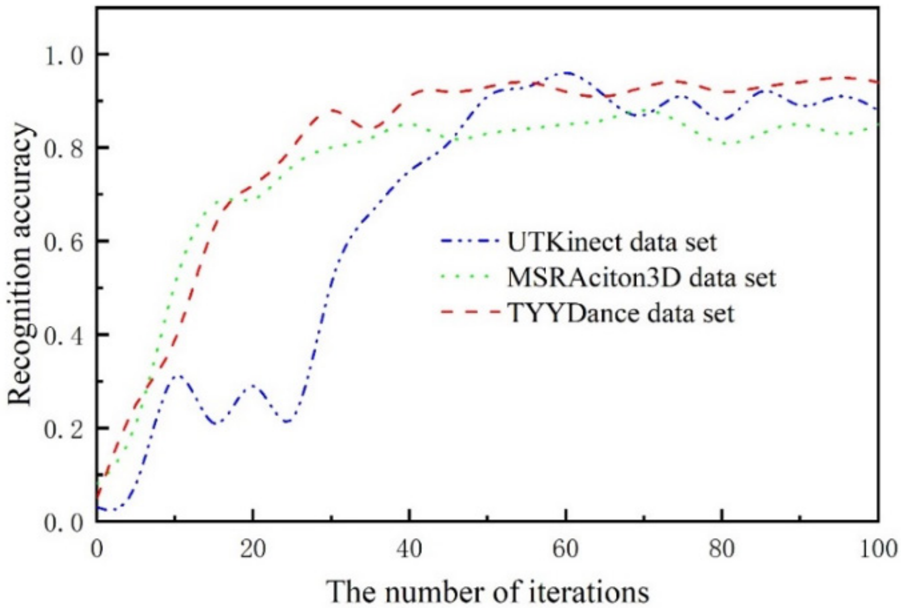

Figure 5. The test recognition rate of three data sets

In the experimental process, the 3D convolutional neural network action recognition algorithm under the machine learning model was trained on the training and validation sets of all subjects, and the loss function curves were obtained as shown in Figure 6.

https://doi.org/10.17993/3ctic.2023.121.267-285

In the figure, the vertical coordinate is the loss value, and the horizontal coordinate is the number of iterations; from Figure 6, we can see that after 45 iterations, the loss gradually stabilizes at about 0.016, which is the best training effect of the model.

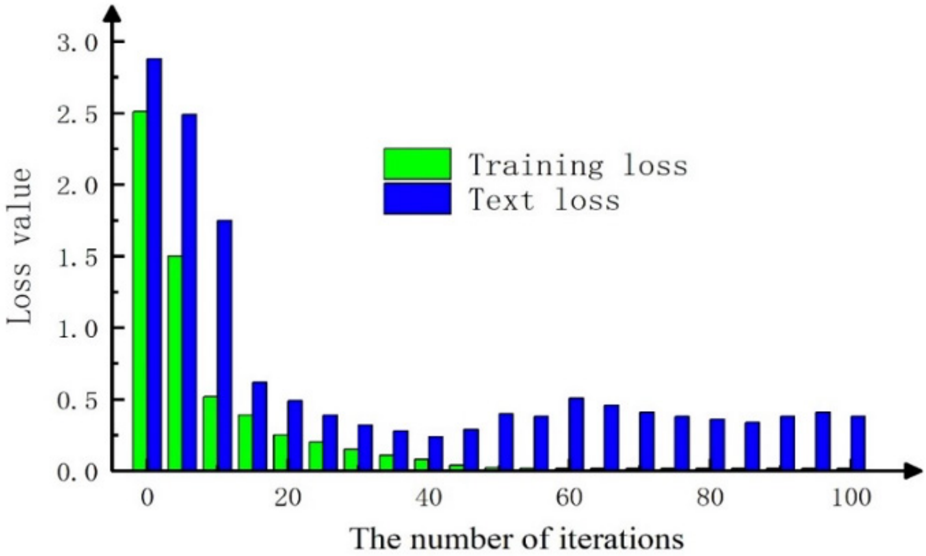

Figure 6. The loss function of the training set and test set

As shown in Figure 7, the graphs of the recognition accuracy functions of the training and validation sets are obtained experimentally. In the graph, the recognition rate of the training set reaches 99.74% after 45 iterations of model training, and then the curve remains stable, reaching the best recognition effect of the model.

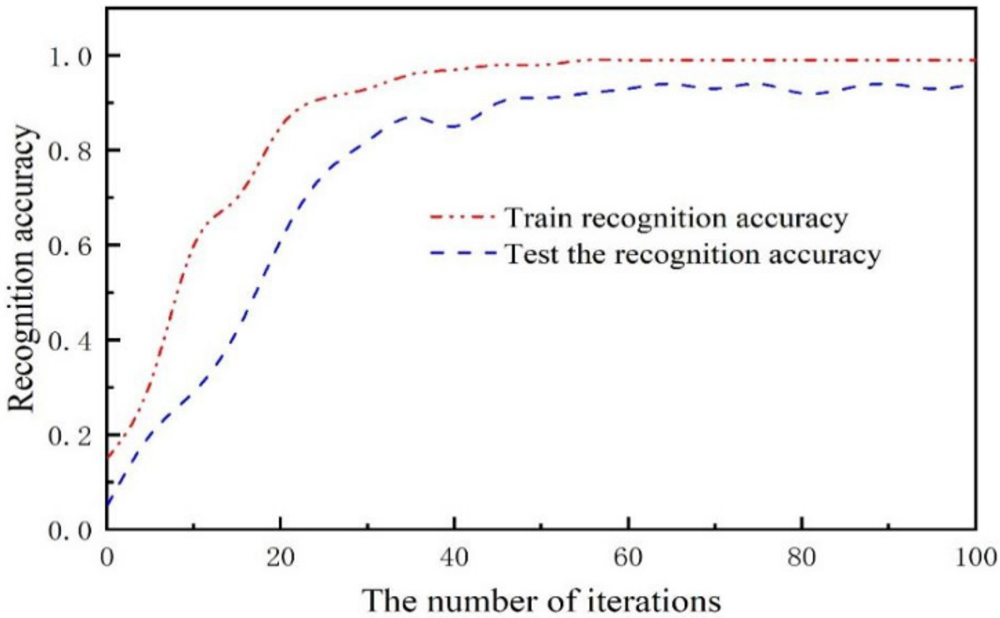

Figure 7. The loss function of the training set and test set

Other classical algorithms also use skeleton data input, and compared with the 3D convolutional neural network action recognition algorithm based on the machine learning model, the results are shown in Table 3, the model used in this paper has

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higher recognition accuracy in the dataset of this paper, which is slightly higher than P3D, about 6% higher than ConvLSTM, and about 3.5% higher than C3D(1net).

Table 3. Compare results with other methods

Methods	Recognition accuracy
C3D(1 net)	91.27%
P3D ResNet	94.29%
ConvLSTM	90.13%
3D CNNs(ours)	96.91%

From the experimental results, we can see that using human skeleton information can occupy less storage space to obtain good recognition results, so each model has good recognition results in the dataset of this paper. Compared with the C3D recognition algorithm model, this paper follows the convolutional kernel small and large 3×3×3, but there are 8 convolutional layers in C3D, and the data volume is too large for the data set in this paper, so this paper adjusts the number of layers and the number of convolutional kernels in the model to obtain better recognition results. This is one of the reasons why the skeleton information of sports dance movements is collected in this paper, and the good results obtained from the experiments in this paper validate the experimental movement collection, as well as the data pre-processing and the rationality of this data set.

5. CONCLUSION

Each kind of sports dance has its own unique culture and spirit, and dance is a way for human beings to use body language to express emotions and convey their feelings, which is a common language for human beings regardless of borders and race. In this paper, a complete process from dance movement data collection to movement recognition is realized, and the typical movement data set is constructed by collecting the typical movement skeleton information of physical dance, excluding the interference of background, lighting and other factors. The experimental results show that the 3D CNNs in this paper can produce satisfactory results for sports dance movement recognition, and validate the feasibility of the 3D convolutional neural network movement recognition algorithm based on a machine learning model in the acquisition to recognition of sports dance movements, which can better open up the content of sports dance education through machine learning model. However, there are still some deviations in the recognition results of a few movements with high similarity, and only some typical movement fragments were collected as data samples for the construction of the dataset, and there is still a lot of research space for the whole performance. Therefore, the next research direction is to use more optimized deep learning algorithms to optimize the recognition of sports dance movements, collect more sports dance movement data to expand the dataset, and to recognize different dance movements in longer dance performances.

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DATA AVAILABILITY

Data for this study are available from the authors upon request.

CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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