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Estimation on Human Motion Posture Using Improved Deep Reinforcement Learning

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Abstract. Estimating human motion posture can provide important data for intelligent monitoring systems, human-computer interaction, motion capture, and other fields. However, the traditional human motion posture estimation algorithm is difficult to achieve the goal of fast estimation of human motion posture. To address the problems of traditional algorithms, in the paper, we propose an estimation algorithm for human motion posture using improved deep reinforcement learning. First, the double deep Q network is constructed to improve the deep reinforcement learning algorithm. The improved deep reinforcement learning algorithm is used to locate the human motion posture coordinates and improve the effectiveness of bone point calibration. Second, the human motion posture analysis generative adversarial networks are constructed to realize the automatic recognition and analysis of human motion posture. Finally, using the preset human motion posture label, combined with the undirected graph model of the human, the human motion posture estimation is completed, and the precise estimation algorithm of the human motion posture is realized. Experiments are performed based on MPII Human Pose data set and HiEve data set. The results show that the proposed algorithm has higher positioning accuracy of joint nodes. The recognition effect of bone joint points is better, and the average is about 1.45%. The average posture accuracy is up to 98.2%, and the average joint point similarity is high. Therefore, it is proved that the proposed method has high application value in human-computer interaction, human motion capture and other fields.

Keywords: estimation, human motion posture, deep reinforcement learning, generative adversarial networks, image labels

1 Introduction

Human posture estimation based on static images is a kind of middle-level vision problem, which needs to comprehensively use the image boundary, image gradient, the significance of the target in the image, image block and other low-level image information [1]. At the same time, constraints and restrictions such as geometric vision and spatial position distribution of the target are applied to obtain the parameters of human postures, such as position, size and angle. In addition, the estimated human posture parameters can be further used as the basic information for analyzing and understanding the high-level semantics of the target behavior [2]. It helps to further analyze behavioral actions, such as video surveillance in public places for crowd activity information, in medical rehabilitation for human activity information, and in the home for daily status monitoring of the elderly. It can be seen that human motion posture estimation is very important for video image analysis and has a wide range of application prospects in the fields of intelligent surveillance systems, human-computer interaction, human motion capture and assisted health evaluation, which is a quite relevant research direction in the field of artificial intelligence research. With the improvement of society's requirements for video analysis and people's deeper understanding of vision systems, human motion posture analysis has become a hot problem in the field of computer vision in recent years.

However, traditional human motion posture estimation uses cameras to capture images of human motion, and relevant personnel to judge and estimate the human motion posture; however, these methods are highly subjective, resulting in poor posture estimation results. The complexity of human motion posture and its dynamic variability is limited in practical application and brings difficulties to the analysis of human motion posture estimation. Therefore, it is an urgent problem to find effective technical methods to describe human motion. Literature [3] proposed a human motion posture estimation algorithm combining sequence-to-sequence (seq2seq) structure and attention mechanism. The seq2seq model is a sequence-to-sequence model based on Gate Recurrent Unit.

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An attention mechanism is added to the decoder part of the seq2seq model to further encode the encoder output as a vector sequence containing multiple subsets, so that the decoder selects the most relevant parts of the sequence for decoding prediction and combines the prediction results to achieve human motion posture estimation. However, there is a problem of high confusion rate of nodes. Literature [4] proposed an algorithm for human motion prediction using an encoder-decoder framework with stacked residual blocks with a small filter for predicting future human posture, which provides the flexibility to capture hierarchical spatial and temporal representations of human motion signals from motion capture sensors. The encoder consists of multiple remaining convolutional blocks stacked to encode the spatiotemporal features of previous postures hierarchically. The decoder consists of two fully connected layers to automatically reconstruct the spatial and temporal information of future posture in a non-recursive manner, which avoids the accumulation of noise unlike previous works. The results obtained using it for human motion posture prediction are more spatiotemporal; however, the overall computation time is long and the practical application is not good.

In recent years deep reinforcement learning has been developed as a combination of deep learning and reinforcement learning with strong understanding of visual problem analysis and excellent decision-making ability of reinforcement learning. Therefore, this paper proposes an estimation algorithm for human motion posture based on improved deep reinforcement learning. The double deep Q network (DQN) is constructed to improve the deep reinforcement learning, which is used for the coordinate positioning of human motion posture, improve the positioning effect of the algorithm, and then realize the estimation of motion posture. The main contributions of this paper are as follows: (1) Double DQN is constructed to improve deep reinforcement learning, which is regarded as the core method of human motion posture coordinate positioning. Compared with the traditional method of posture judgment and estimation using camera capture, it improves the computational performance and accuracy of the algorithm, and fundamentally solves the problem of abnormal joint point estimation results.(2)The motion posture discriminator generator is set to control the processing link of human motion images to enhance the processing of complex and diverse human motion posture images as a way, and to improve the effectiveness of human motion posture estimation.(3)Experiments are conducted based on the MPII Human Pose data set as well as the HiEve data set to verify the effectiveness of the application of the proposed algorithm by comparing several metrics.

2 Related Works

With the continuous deepening of the research on human motion posture, people's requirements for the accuracy of human motion posture estimation results continue to improve, and most of the research in this field is carried out around this content. For example, Literature [5] proposed a human motion prediction algorithm combining recurrent neural network (RNN) and inverse kinematics, which combines RNN and inverse kinematics to predict motions of human arms. The improved Kalman filter is used to adjust the model online, and the human motion prediction is realized by combining the prediction results. This algorithm reduces the error of human motion posture estimation to some extent, but it has the problem of low accuracy. Literature [6] proposed a human motion posture prediction algorithm using RNN. A new diffusion convolution recursive predictor for spatial and temporal motion prediction is designed based on RNN. The multi-step random walk traverses the adaptive graph Bi directionally to analyze the interdependence between body joints. A forward discriminator is added to the forward predictor to alleviate this kind of motion drift for a long time in antagonistic training. When it is applied to human motion position estimation, the low dynamic motion trend can be estimated, but the Percentage of Correct Keypoints (PCKh) is low. Literature [7] proposed a human motion prediction algorithm using an encoder-decoder framework with stacked residual blocks. The framework has a small filter for predicting future human posture, which can flexibly capture hierarchical spatial and temporal representations of human motion signals from motion capture sensors. The encoder is stacked by a plurality of residual convolutional blocks to encode the spatiotemporal features of the previous pose hierarchically. The decoder is composed of two completely connected layers, which can automatically reconstruct the spatial and temporal information of future postures in a non-recursive way, which can avoid the accumulation of noise different from previous works. The results of human motion posture prediction using this method are spatiotemporal, but the overall operation time is long, and the practical application effect is not good. Literature [8] proposed a multiscale graph convolution to aggregate human motion posture neighbor features at different distances and applied it to nodes with specified neighbor types, and further proposed a hierarchical body pool to aggregate and share body-level and body-part-level contextual information. Finally, a lightweight three-dimensional posture map convolution network is developed by overlapping the multi-scale image convolution residual block and the layered pool layer. The algorithm runs for a long time. Literature [9] established the posture estimation algorithm based on DeepLabCut (an open so open-source estimation toolkit), which provides the tracking function required for multi-pose scenarios, but ignores the problem of joint point estimation, and the joint point similarity is low; Literature [10] analyzed the human motion posture tracking algorithm. This paper used the human tracking algorithm named OpenPose to detect joint points, measure joint segments and joint angles, and verified the effectiveness of human posture tracking in the running gait analysis system, but the positioning accuracy of joint nodes is not high; Literature [11] proposes a human posture estimation method based on two-branch network in the clothing scene. This paper adds multi-scale loss and feature fusion output joint point score map based on the stacked hourglass network to solve the interference of complex background on the image. The loss function is established to solve the problem of posture and angle change. Finally, the estimation result is obtained through posture optimization, but the complexity of the calculation process leads to relatively long time; The literature [12] introduced a multispectral attention mechanism based on Lite-HRNet and designed a lightweight high-resolution human posture estimation network Lite MSA-HRNet combined with multispectral attention mechanism, which has obvious advantages for the extraction of human posture feature information and fast network localization, but the degree of confusion for human motion posture nodes is relatively high, which affects the calculation results.

Therefore, an algorithm for estimation of human motion posture based on improved deep reinforcement learning is proposed in this study. The results show that the proposed algorithm has higher joint node localization accuracy, good skeletal joint point recognition, PCKh value does not exceed 0.5, the average human motion posture joint point confusion rate is about 1.45%, the average posture correct rate is up to 98.2%, the average joint point similarity is high, the algorithm running time is short, the F value is up to 0.93, and the overall performance is superior.

3 Methodology

3.1 The Framework of Proposed Algorithm

Human motion posture estimation is an important research area in the field of computer vision, and it has become a popular research topic to obtain more efficient posture estimation results by using cutting-edge technology. Therefore, we focus on human motion posture estimation and propose a human motion posture estimation algorithm based on improved deep reinforcement learning, and the framework of this paper is shown in Fig. 1.

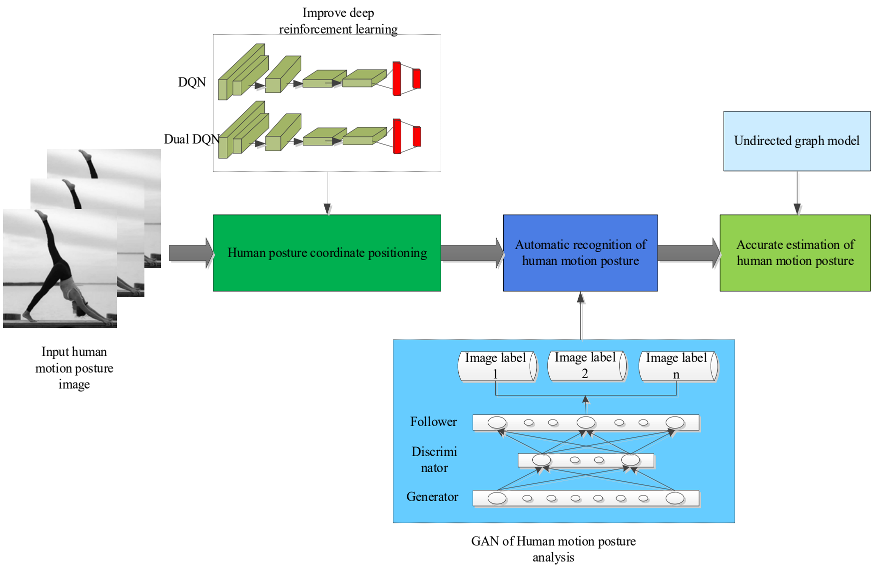


Fig. 1. The framework of human motion posture estimation

As can be seen from Fig. 1, after inputting human motion posture images, this paper establishes a dual DQN to improve deep reinforcement learning, and uses the improved method for coordinate localization. Then the human motion posture analysis generating adversarial network is constructed by generator, discriminator and follower to complete the automatic recognition of human motion posture, based on which the human motion pose estimation is realized.

3.2 Positioning of Posture Coordinate

In the estimation of human motion postures, it is necessary to first determine the coordinates of each bone point in human motion posture and calibrate it. However, during the calibration process, the coordinates of key points will be lost due to improper operation. Therefore, in this study, the improved depth reinforcement learning algorithm is used to compensate for the loss in joint calibration.

The deep convolution neural networks and the fully connected neural network are used to realize typical deep reinforcement learning. The original training data are input, the agent mechanism is introduced to improve the deep reinforcement learning algorithm, and the state action Q function is output to realize the optimization of human motion posture coordinate points. To improve the learning efficiency and real-time performance of the deep reinforcement learning algorithm, the dual DQN is introduced to build a dual DQN, whose loss function is equivalent.

$$L(\theta)=E_s\left[\left(Q^*\left(s,a|\theta\right)-y_i\right)^2\right], \tag{1}$$

where E_s refers to the learning rate, $Q(s, a)$ refers to the Q value function when implementing action a under status s, y_i is the dual DQN value calculated according to the previous iteration cycle, and θ denotes sample transfer rate.

After integrating the dual DQN, the parameters in dual DQN are defined as θ^Q, $\theta^Q(s, \mu(s))$ refers to the expected return value obtained after selecting action by adopting strategy μ under the status s. And because it is in a continuous space, it is expected to be solved by integral. Therefore, the following Equation can be used to express the quality of the strategy μ

$$J_\beta=\int_{-\infty}^{\infty}\rho^\beta\left(s\right)Q^Q\left(s,\mu\left(s\right)\right)ds\,, \tag{2}$$

where ρ^β refers to the integral density. Then the improved deep reinforcement learning is applied to the joint coordinate positioning process. The loss function is expressed by the following Equation

$$r=\arg\min\left\|x_i+b-\beta(y_i)\right\|^2. \tag{3}$$

where r refers to the loss function of the joint coordinate; (x, y) refers to the vertical and horizontal coordinates of the joint; x_i refers to the data about human joint in the image; y_i is the position of human joint; $\beta(y_i)$ refers to the joint coordinate obtained from calculation. According to this Equation (3), the final calibration results of joint points can be obtained

$$E=\frac{(\varphi(x),\varphi(y))}{(x,y)}, \tag{4}$$

where $(\varphi(x), \varphi(y))$ refers to the result of image normalization [13]. According to Equation (2), all images within the training set are processed and the human motion posture labels in the images are set, and the calculation process is set as follows

$$E(x,y)=\begin{bmatrix}\frac{1}{\varphi(x)} & 0\\ 0 & \varphi(y)\end{bmatrix}\frac{(\varphi(x),\varphi(y))}{(x,y)}. \tag{5}$$

Equation (5) is used to construct the motion posture labels of each image, the problem of poor calibration ability of bone points in human motion posture recognition is further improved, which provides the basis for the subsequent image processing and calculation process [13].

3.3 Construction of Human Motion Posture Analysis Generative Adversarial Networks (GAN)

Based on the image processing results, a human motion posture analysis and GAN is constructed [14-15], and the motion posture discrimination generator is set to realize the automatic recognition and analysis of human motion postures. To ensure that the application effect of the generator meets the requirements of image processing, the image loss function of the generator is calculated. The calculation process is as follows

$$L(\wp,m)=\frac{\left|\frac{1}{\wp_i}-\frac{1}{m_i}\right|}{n}, \tag{6}$$

where $\wp$ refers to the prediction result of the bone point; m is the label of motion posture; n refers to the number of bone joint marker points. Using Equation (6) to check the posture labels generated by the generator. After this calculation link is completed, set the discriminator loss function to control its application effect. At this time, there are

$$U=L\left(\frac{d(x,y)}{y}\right)-L\left(\frac{d(x,\bar{y})}{\bar{y}}\right), \tag{7}$$

where $d(x, y)$ refers to the positive output result of the discriminator; $d(x,\bar{y})$ represents the negative output result of the discriminator [16]. Integrate the contents of Equation (4) and Equation (5) to generate the parameter update Equation for the GAN based on the analysis of human motion posture

$$\varpi_{i+1}=\varpi_i+\rho\left(L\left(\frac{d(x,y)}{y}\right)-L\left(\frac{d(x,\bar{y})}{\bar{y}}\right)\right), \tag{8}$$

where ϖ_i refers to the coefficients to be set in the network; ρ refers to the updated iterations of network parameters. This Equation is used to optimize the parameters for generating the GAN. At the same time, the processed images are imported into the network, and the labels of the images are sorted and analyzed to provide an image basis for the subsequent human motion posture prediction.

3.4 Construction of Human Motion Posture Analysis GAN

Based on the above content, an estimation algorithm of human motion posture is designed. The implementation process of the algorithm is as follows:

Input: Human image

Output: Estimation results of human motion posture

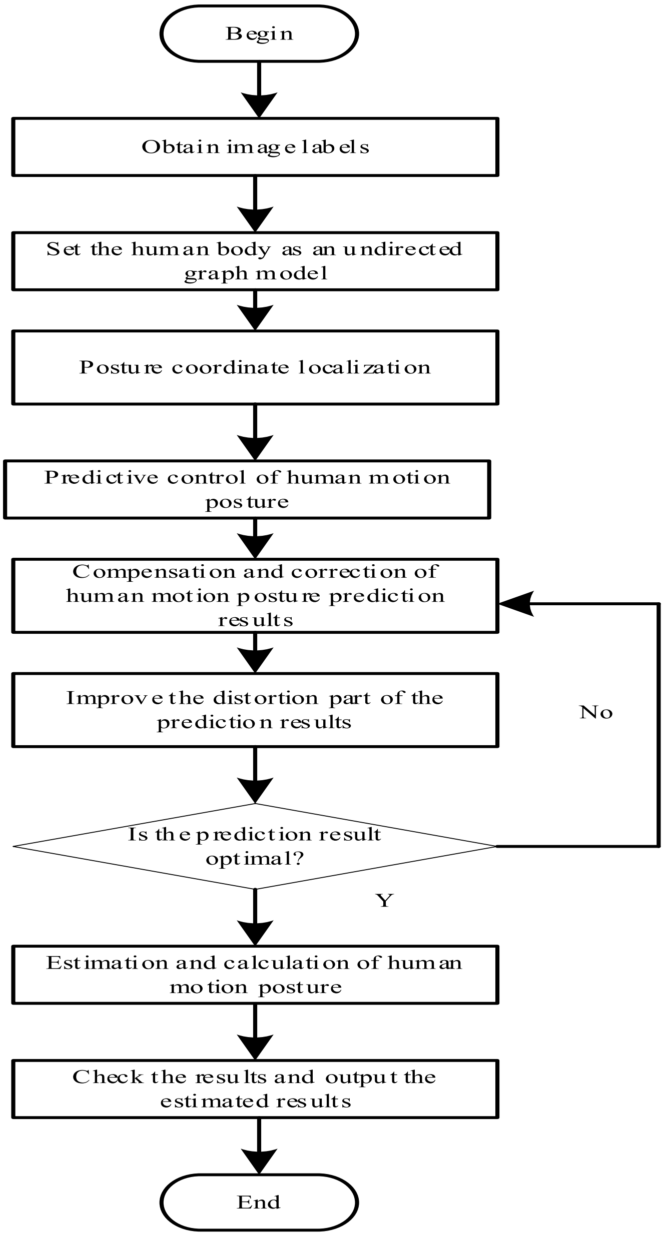


Fig. 2. Process of estimation of human motion posture

To make full use of the preset human motion posture tag, the human is set as an undirected graph model [17-18] in the process of motion posture estimation. The details are as follows

$$G = (S, B), \tag{9}$$

where S contains a large number of human joints. Combined with the posture coordinate positioning results based on improved deep reinforcement learning, the changes in human joint points are analyzed as follows

$$J = \frac{\left\| R_{ij} - G_{ij} \right\|^2}{N}, \tag{10}$$

where R_{ij} is the true value of joint points in motion; G_{ij} denotes the prediction result of human motion posture; N refers to the number of human joint points in the image. After the prediction is completed, the following correction Equation is used to control the prediction results according to Literature [19]. Then

$$L' = \frac{\sum_{n=1} \left\| (R_x, R_y) - (G_x, G_y) \right\|}{N}, \tag{11}$$

After the calibration is completed, set the human motion position prediction result compensation correction function

$$V = L' + \lambda L_x + \phi L_y, \tag{12}$$

where λ and ϕ refers to constraint coefficient in image compensation. This Equation can be used to improve and optimize the distortion in the prediction results. By integrating the above contents, the design of the estimation algorithm of human motion posture based on improved deep reinforcement learning has been completed, as shown in Fig. 2.

4 Experimental Analysis and Results

Aiming at the shortcomings of the current estimation algorithm of human motion posture, an estimation algorithm for human motion posture based on improved deep reinforcement learning is proposed. An experimental session is constructed to verify the application performance of this method and analyze its advantages and disadvantages to provide a case study for subsequent research.

4.1 Data Sets and Evaluation Indicators

In this experiment, two human motion image data sets were used. After many comparisons, HiEve data set and MPII human pose data set were selected as the data basis of this experiment. Among them, the MPII human pose data set contains 10000 images, and the images in this dataset contain bounding boxes, to avoid the human posture estimation algorithm can process the correct objects. Two thousand images in the data set are randomly selected as the training set, and two hundred images are the test set. To improve the authenticity of the experiment, the data set does not provide information on the number and size of people in the image. HiEve data set includes various crowd posture data in complex events (including subway boarding and alighting, collision, combat and earthquake escape). HiEve data set includes the current maximum number of postures, and the largest number of complex event action tags, and is one of the largest numbers of tracks with the longest duration, with an average track length greater than 480. The images in the dataset are manually labeled on the upper of the human. Two thousand images in the HiEve dataset are randomly selected as training set, and two hundred images are used for test set. Collate the above experimental data sets, and take the collated data as the data basis of this experiment.

To evaluate the application effects of different human motion posture estimation algorithms, five groups of evaluation indexes are set to evaluate the calculation links and results of human motion posture estimation algorithms, and determine the advantages and disadvantages of different methods.

PCKh values: The proportion value correctly estimated by key points is an important index to measure the performance of human motion posture estimation. The PCKh value is obtained by normalizing the Euclidean distance between the prediction result and the target image. In this experiment, it is used as the objective evaluation index of human motion posture estimation algorithm. Let the calculation threshold of this indicator be 0.5. When the calculation result exceeds this threshold, it indicates that the joint point estimation result is wrong. The calculation Equation of this indicator is set as follows

$$t = \frac{\left| u - \bar{u} \right|}{q}, \tag{13}$$

where u refers to the actual motion value of a certain human joint in the image; $\bar{u}$ is the predicted motion value of a certain human joint in the image; q refers to the diameter of human head in the image; t stands for the calculation threshold value.

Algorithm running time: Because the overall process of human motion posture estimation is complex, the time complexity is used to reflect the overall running time of the algorithm. The Equation is as follows

$$t=\left|t_1 \text{-} t_2\right|, \tag{14}$$

where t_1 and t_2 refer to the algorithm ending time.

Confusion rate of joint points in human motion posture: In previous studies, most human motion posture estimation algorithms often have the problem of confusing the left and right bone nodes of the human. Therefore, the human motion posture joint confusion rate is taken as an important performance evaluation index of the estimation algorithm. The calculation Equation is as follows

$$c = \frac{K_i}{K_{all}} * 100\%, \tag{15}$$

K_i refers to the wrong left and right bone joints; K_{all} is all the human joints; c denotes the confusion rate of human motion posture joints.

Posture estimation accuracy (PEA): The posture estimation accuracy value represents the posture accuracy of the motion posture estimation results. Therefore, this Equation can be used to determine whether the distance estimation results between bone points are reasonable, to determine the calculation accuracy of the estimation algorithm

$$A = (p_2 * p_3)\frac{1}{p_1}, \tag{16}$$

p_1 refers to the number of joint point distances around the correct motion posture point; p_2 refers to the total number of joint point distances marked by human motion posture in the image; p_3 is the total number of images.

Average joint point similarity: Due to the absolute error of PCKh, in this experiment, the joint points of different human bones and the size of human images are normalized to obtain the average joint point similarity in human motion posture estimation. The calculation Equation is as follows

$$E = \frac{\exp \dfrac{\alpha}{-d_i * 2lh}}{\sum_i \alpha}, \tag{17}$$

where d refers to the distance between key bone point coordinates and predicted key bone points; h refers to the area of the image in the image; l is the normalized calculation coefficient; α is the visible coefficients of key points. During the calculation of this index, the closer the value is to 1. It shows that the results of the estimation algorithm are more similar.

F-measure: To further verify the overall performance of the algorithm in this paper, the weighted harmonic average F-measure of recall and accuracy is selected as the evaluation index to compare and analyze different algorithms. The calculation formula of F-measure is as follows

$$\text{F-measure} = \frac{Rec \cdot Accu}{Rec + Accu}, \tag{18}$$

where Rec is recall of human motion posture estimation. $Accu$ represents the accuracy of human motion posture estimation.

The evaluation indexes set above are sorted out and taken as the main evaluation content of the use effect of the estimation algorithm of human motion posture in this experiment.

4.2 Experimental Scheme

The experimental data set is screened and cleaned to filter out invalid data and enhance useful data, while normalizing all data sets to facilitate the unified calculation of subsequent data. Finally, the completed data after processing is used as the database for this experiment. The image size in the experimental data set is uniformly set to 1080*1080*5, and the RMSProp optimizer is used to optimize the image processing. The image batch is set to 10, and each round of training images is recorded as an iterative calculation. The overall human motion posture estimates the number of calculation iterations and sets it to 100. The learning rate was initialized to 0.001 and decreased by 30 times at the 50^{th}, 75^{th} and 100^{th} times, respectively. In this experiment, the weight decay factor of the improved deep reinforcement learning model is 0.00005 and the momentum factor is set to 0.7.

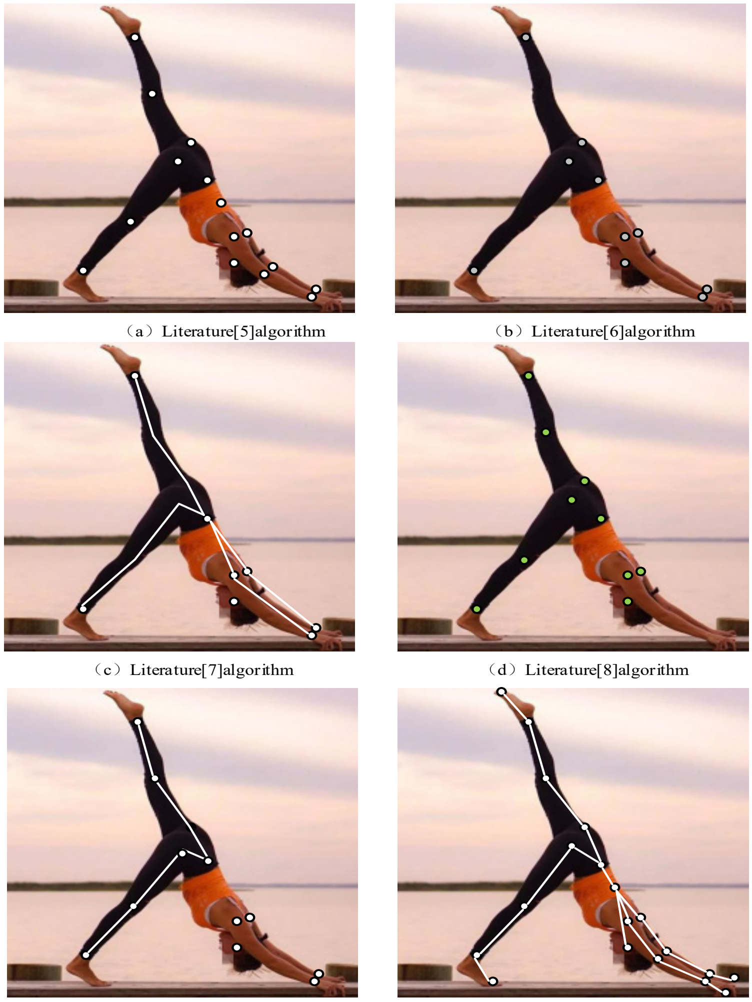
To improve the contrast of the experiment, five other algorithms are selected in this experiment to compare with proposed algorithm, and the algorithms involved in the experimental comparison are the algorithms of literature [5], literature [6], literature [7], literature [8], and literature [9]. To better complete the experiment, a representative image is selected as the target image, a variety of estimation algorithms are used to process the target image, and the estimation results are obtained to provide an image basis for subsequent experimental analysis. It is shown in Fig. 3.

Fig. 3. Target image

As some indicators selected in this experiment have high requirements for human bone points, to realize the analysis process of these indicators, this key joint point is set as elbow joint (recorded as joint 1), knee joint (recorded as joint 2) and hip joint (recorded as joint 3), to reduce the difficulty of experimental calculation. At the same time, in the calculation process of index (3), to avoid the impact of a large amount of image calculation on the accuracy of experimental results, only the processing results of the target image are analyzed. According to the above experimental scheme, the experimental operation process is completed, and the experimental results are obtained and analyzed to determine the application effects of different estimation algorithms.

4.3 Results and Discussion

An image in the HiEve data set is randomly selected as the experimental object, and the motion posture of the target image is estimated using the algorithm selected. The results are shown in Fig. 4.



(a) Literature[5]algorithm (b) Literature[6]algorithm
(c) Literature[7]algorithm (d) Literature[8]algorithm
(e) Literature[9]algorithm (f) Proposed algorithm

Fig. 4. Comparison results of target image

According to Fig. 4. There are obvious differences in the results of different motion posture estimation algorithms, and the number of joint points detected in this paper is the highest among the six algorithms, which is 19. It is 4, 9, 11, 9 and 8 higher than the algorithms in Literature [5], Literature [6], Literature [7], Literature [8] and Literature [9], respectively, indicating that the algorithm detects more joint nodes and has higher positioning accuracy. The reason is that this method uses the dual DQN to improve the deep reinforcement learning algorithm, locates the position of posture coordinates, and improves the effect of bone point calibration. The results of PCKh values calculated for different algorithms are shown in Table 1.

Table 1. Comparison results of PCKh value

Algorithms	MPII human pose data set			HiEve data set		
	joint 1	joint 2	joint 3	joint 1	joint 2	joint 3
Proposed	0.25	0.37	0.36	0.40	0.37	0.28
Literature [5]	0.41	0.46	0.48	0.52	0.47	0.46
Literature [6]	0.42	0.50	0.51	0.35	0.34	0.55
Literature [7]	0.42	0.35	0.39	0.50	0.55	0.54
Literature [8]	0.45	0.62	0.48	0.60	0.47	0.43
Literature [9]	0.50	0.55	0.48	0.26	0.34	0.51

According to the data in Table 1. The PCKh value obtained by proposed algorithm of MPII human pose dataset and HiEve dataset does not exceed 0.5, indicating that the accuracy of the estimation results of proposed algorithm is high.

Compared with other algorithms, the algorithms in literature [5], literature [6], literature [7], literature [8], and literature [9] show one or more calculation results exceeding the threshold at different joints, indicating that the estimation correctness of this part of the method is relatively low and the obtained results are less reliable than the proposed algorithm. Meanwhile, according to Fig. 4, it can be seen that the skeletal joint point recognition ability of different algorithms varies widely, and the upper limb joint recognition ability of the algorithm of literature [8] and literature [9] is poor, and the lower limb joint point recognition ability of the algorithm of literature [6] and literature [7] is poor. With Equation (15), the confusion rate of joint points of human motion posture in different methods in Fig. 4 is analyzed, and the results are shown in Fig. 5.

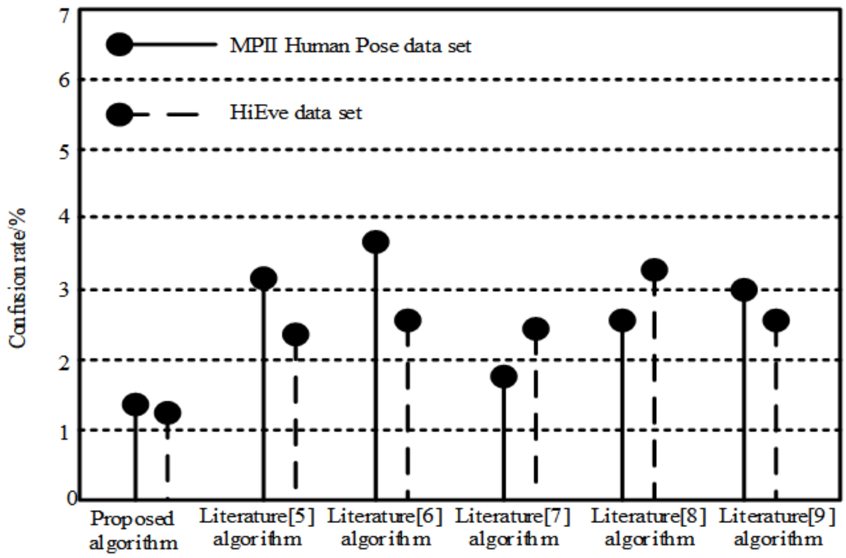


Fig. 5. Comparison results of joint point confusion rate of human motion posture

The confusion rate of human motion posture joints is consistent with the analysis results in Fig. 5. The proposed algorithm has a low confusion rate of human motion posture joint points, which is about 1.45% on average. For MPII human pose dataset, the human motion posture joint point confusion rate of the algorithm in this paper is 2.1%, 3.4%, 1.5%, 1.3% and 1.7% lower than that of algorithms in Literature [5], Literature [6], Literature [7], Literature [8] and Literature [9]; For the HiEve dataset, the human motion posture joint confusion rate of this algorithm is reduced by 1.1%, 1.4%, 1.2%, 2% and 1.3%, respectively compared with the algorithms in Literature [5], Literature [6], Literature [7], Literature [8] and Literature [9]. At the same time, Fig. 5 shows that the algorithm in this paper has a stable effect on the two data sets, and other algorithms are highly dependent on the types of data sets. This result proves that this algorithm has some computational advantages. Based on the experimental results, the calculation results of PEA value index are obtained, as shown in Table 2.

Table 2. Comparison results of PEA value

Algorithms	MPII human pose data set			HiEve data set			Average value
	joint 1	joint 2	joint 3	joint 1	joint 2	joint 3	
Proposed	98.5	98.0	97.9	98.2	98.0	98.5	98.2
Literature [5]	96.1	96.5	96.7	97.0	97.1	97.8	96.9
Literature [6]	96.0	95.8	95.9	96.0	96.1	96.5	96.1
Literature [7]	96.3	96.5	95.8	95.1	94.6	94.5	95.5
Literature [8]	94.6	95.6	95.8	96.0	94.5	94.5	95.2
Literature [9]	96.1	95.8	95.6	94.2	94.5	96.1	95.4

According to the data in Table 2. During the experiment, the average posture accuracy of the proposed algorithm is 98.2%, while the posture accuracy of other algorithms is relatively low. The average posture accuracy rate of algorithms in literature [5] and literature [6] is about 96.0%, and that of algorithms in literature [7], literature [8] and literature [9] is about 95.0%. The results supplement the experimental results of PCKh value, and confirm the advantages of the proposed algorithm. The data in Table 1 and Table 2 are fused and analyzed to obtain the average results of joint point similarity, as shown in Fig. 6.

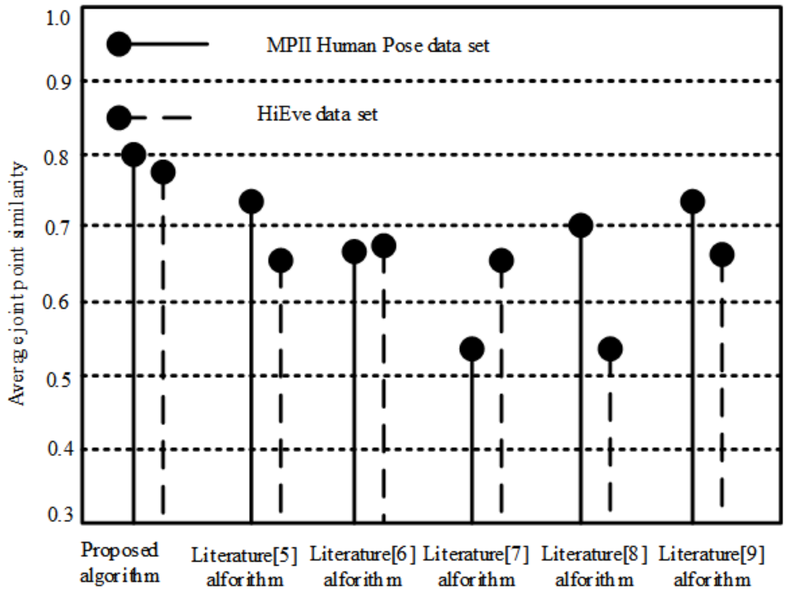


Fig. 6. Comparison results of average joint point similarity

According to the data in Fig. 6. The average joint point similarity of the results obtained by the proposed algorithm is consistent with the experimental comparison algorithm. For MPII human pose data set, the average joint point similarity of the proposed algorithm is 0.6, 1.3, 2.7, 1, 0.7 higher than that of algorithms in Literature [5], Literature [6], Literature [7], Literature [8] and Literature [9]; for the HiEve dataset, the average joint point similarity of the proposed algorithm is 1.3, 1, 1.3, 2.5 and 1.2 higher than that of algorithms in Literature [5], Literature [6], Literature [7], Literature [8] and Literature [9], respectively, which proves that the estimation results of proposed algorithm are relevant and consistent. The results of average joint point similarity obtained by other algorithms are relatively low, indicating that the correlation between the estimated results obtained by other methods and the target image is low, and the authenticity of the estimated results is poor. Through the comprehensive analysis of the experimental results of PCKh value, PEA value, average joint point similarity and human motion posture joint confusion rate of different algorithms, it can be determined that the computing power of proposed algorithm is better than that of other algorithms. The overall performance of the algorithm is analyzed, and the operation time of different algorithms is counted. The results are shown in Table 3.

Table 3. Running time of human motion posture estimation algorithm (min)

Algorithms	MPII human pose data set	HiEve data set
Proposed	3.15	0.85
Literature [5]	4.62	1.35
Literature [6]	4.57	2.01
Literature [7]	4.68	2.31
Literature [8]	4.98	2.64
Literature [9]	5.01	3.15

According to the data in Table 3. Because there are many images in MPII human pose dataset, the overall running time of all algorithms used in the experiment is longer than that of HiEve dataset. However, the running time of the proposed algorithm is shorter than that of other algorithms in two data sets. For the MPII Human Pose data set, the running time of the proposed algorithm is 3.15min, and the running time of other algorithms is between 4.57-5.01min. For the HiEve dataset, the proposed algorithm's running time is 0.85min, and that of other algorithms is 1.35-3.15min, indicating that the computational efficiency of this algorithm is relatively high. It can be determined by combining the results with the above multiple groups of indicators. The proposed algorithm is superior to other methods in terms of computational accuracy and speed. The calculation results of F-measure of different algorithms are shown in Fig. 7.

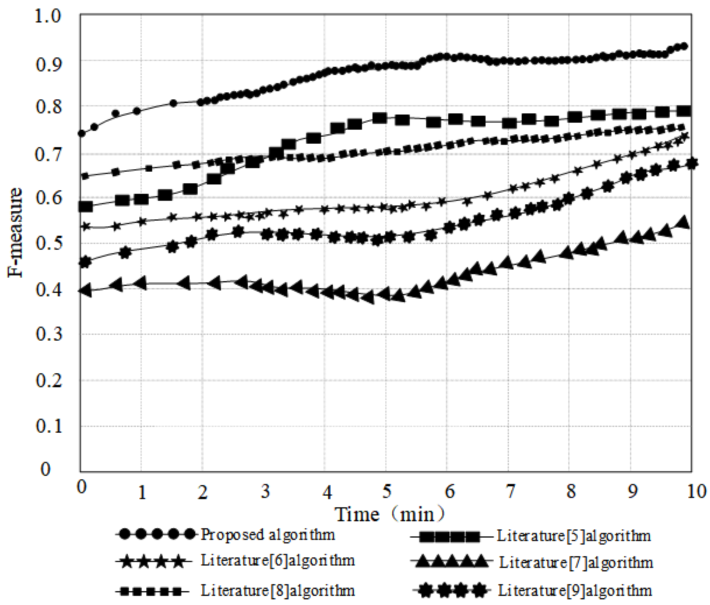


Fig. 7. Comparison of F-measure of different algorithms

According to analysis results in Fig. 7, it can be seen that the F-measure curve of the proposed algorithm is always higher than that of other algorithms, and the highest value reaches 0.93, which is far higher than that of the comparison algorithms. The F-measure of the algorithms in literature [5], literature [6] and literature [8] is relatively high, but the maximum value is not more than 0.8. The F-measure curve of the algorithm in literature [7] is at the lowest point, not reaching 0.5, and the maximum value of the algorithm in literature [9] is not more than 0.7. The above comparative analysis shows that the algorithm based on improved deep reinforcement learning for human motion posture estimation has a good effect.

5 Conclusions

Human motion posture analysis plays a key role in deeply understanding human motion status and better application in human-computer interaction, home monitoring, medical assistance and other fields. Given the limitations of existing human motion posture estimation methods, this paper proposes a human motion posture estimation algorithm based on improved deep reinforcement learning. We construct a dual DQN to improve deep reinforcement learning to complete the human motion posture coordinate localization and improve the localization accuracy; we construct a human motion posture analysis to generate adversarial network to complete the posture recognition and improve the processing effect of complex and diverse human motion posture images; finally, the algorithm analysis is completed using the human motion posture tag. The results show that the average PCKh of the algorithm is 0.34, the joint confusion rates of the two data sets are 1.4 and 1.2, respectively, the average PEA is 98.2%, and the average joint point similarity of the two data sets is 0.80 and 0.78, respectively. The average running time of the human motion posture estimation algorithm is 2.00min. It shows that the proposed algorithm can achieve the goal of fast estimation of human motion posture, and a variety of problems existing in the current algorithm are solved. However, due to technical limitations, the modal analysis of human motion posture in this study is not detailed enough, and the analysis of modal characteristics and related factors is insufficient. Therefore, in future research, more comprehensive consideration needs to be made to provide more data support for human motion posture analysis.

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