Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org
© 2024 SCPE. Volume 25, Issues 4, pp. 2385–2397, DOI 10.12694/scpe.v25i4.2819

APPLICATION OF HUMAN POSTURE RECOGNITION ALGORITHMS BASED ON JOINT ANGLES AND MOVEMENT SIMILARITY IN SPORTS ASSESMENT FOR PHYSISCAL EDUCATION

WEN YAN*, XIAOJING CAO†, AND PENG YE‡

Abstract. The poor application effect of traditional sports training methods and the difficulty of recording data due to the time and space constraints of sports make it difficult for trainers to improve their learning outcomes. Based on this, the study proposes to apply human posture recognition in sports teaching design, and use VGGNet-19 as a feature extractor and OpenCV open source software to capture posture movements, and introduce the concepts of joint angle and movement similarity to design a sports assessment system for physical education based on the geometric spatial feature variability analysis of posture based on limb angle information. The testing outcomes demonstrate that the study's improved gesture recognition algorithm has a recognition rate of more than 90% on gesture movements, and the maximum recognition error value (0.010) is smaller than that of the dynamic time-regularised gesture algorithm (0.014) and the convolutional neural network algorithm (0.017). The assessment system is also better able to improve students' professional performance and satisfaction, with its average professional score and satisfaction reaching 86 and 92%, which is significantly better than other comparative algorithms. The method is effective in providing trainers with data-based training scenarios and helping them to improve their learning in sport.

Key words: Joint angle; Movement similarity; Human posture recognition algorithm; Physical education; assessment system

1. Introduction. Movement as a dynamic body change is based on the movement of a few key parts to demonstrate different teaching movements, so the piecing together and tracking of joint parts is a good way to depict the general work [1]. The design of a movement system to aid training will therefore allow the trainer to learn independently with less time and space constraints, and the trainer will be able to adjust their training plan and intensity in real time based on the training data. [2-3]. The human eye is the most common method of recording, but it is less accurate and less realistic. As an important means of acquiring information, computer vision, as an important branch of information science, is able to extract important feature information from the original image data, which has an important role in object recognition and image reconstruction [4]. Additionally, due to the quick advancement of computer technology, it is now possible to use pertinent artificial intelligence techniques in sports training, where vision techniques can be used to accurately assess and calculate sports types, sports movements, and athlete tracking. Human Pose Estimation (HPE) is a computerised image processing technique that identifies and locates the human body and its articulation points and realises the skeleton of the articulation points [5]. Based on this, the study proposes to apply human posture recognition in sports evaluation and reduce the recognition errors caused by individual differences and difficulties in continuous frame extraction based on joint angles and movement similarity. A sports assessment system is also designed to help learners improve their quality and mastery of sports movements.This article mainly studies the cable current carrying capacity from four aspects. The first part is a summary and discussion of some current algorithms related to human posture recognition and related sports teaching and evaluation. The second part introduces joint angle and motion similarity on the basis of the original pose recognition algorithm, and uses VGGNet-19 feature network for feature extraction, and constructs an evaluation system that meets the needs of physical education teaching. The third step is organising the results after analysing the simulation results and evaluating the developed recognition model's algorithm performance. A summary of the full essay is in the last section.

*College of Business Administration, Xuzhou College of Industrial Technology, Xuzhou, 221140, China (Yw13814440452@126.com)
†Physical Education and Arts Department, Xuzhou College of Industrial Technology, Xuzhou, 221140, China
‡Physical Education and Arts Department, Xuzhou College of Industrial Technology, Xuzhou, 221140, China

2. Literature review. For 2D image pose detection, Nasr M scholars implemented part confidence map detection with the help of part affinity fields associated with parts, and the architecture method showed good application performance and efficiency [6]. With the aid of a multi-way matching technique, dong J scholars clustered 2D poses, and they also developed a view matching approach based on convex optimisation and geometric appearance. The results revealed that the system performed well on the dataset. In order to forecast the network topology, Chen T provided a 3D approach for estimating human pose, and he also implemented a full convolutional propagation structure with long hop connections. Pagnon D proposed a markerless Pose2Sim to improve the recognition accuracy of athletes' movements in the field, which takes a multi-view OpenPose 2D pose as input to calibrate the camera for joint coordinate measurement. The results showed that the standard deviation and mean absolute error of the method were small under different environmental conditions [9]. Luvizon D C scholars proposed a multitasking framework combining monocular colour images and multidimensional human pose with decoupling to achieve prediction of key components. The results show that the method shows good effectiveness on the dataset and can be adapted to multi-target tasks [10]. Pan T Y scholars used Myo armband wearing to make judgments on sports game referee signals, and its final recognition results were obtained by recognising the referee signal gestures and feature extraction by deep belief networks. The experiments showed that the method could better achieve hierarchical processing and training of multimodal data features [11]. Bakshi A scholars proposed a yoga coach design based on pose estimation, and used body key points to achieve region vector mapping, and identified sliced key points with the help of cause estimation model, and applied the method to pose recognition and detection such as squatting and forward bending. The method is better able to recognise postures in different states [12].

Yi X proposed a DNN-based capture method that included global translation and body pose to address the drawbacks of inertial inertial sensing technology for motion capture. The quantitative results showed that the method has better accuracy and efficiency than the learning optimization-based method and expands the sensor's motion spatial environment scale [12]. To overcome the issue that 3D human pose recognition is impacted by high resolution when deep learning is used, Xu X proposed a combination of resolution-aware network, self-supervised loss, and learning scheme. This extended method can better process low-resolution image video, effectively enhance the consistency of deep features, and has better application in pedestrian recognition [13]. qiu Z scholars proposed dynamic graph convolution module (DGCM) to strengthen the connection of key points of multi-person pose estimation recognition. The relationship between all edges of the image and the pose is considered. The outcomes demonstrated that the method's value-added magnitude effect on the test data was greater than 3% [14]. Papic C scholars implemented the analysis of sports videos with the help of neural networks and found that the method could effectively achieve the recognition and detection of body marker positions and greatly reduce the motion analysis time [15]. Mujahid Researchers combined the YOLO v3 and DarkNet-53 networks to recognise gestures, and the findings revealed that the strategy had improved accuracy and recall while requiring less image pre-processing and filtering [16]. Su H proposed a gesture recognition method combining deep visual learning and EMG signal-based gesture recognition, which made its recognition method consider less motion order. And the outcomes demonstrated that the method had greater application efficacy and minimised the step of data pre-annotation [17]. Yan G et al. implemented the HSV space method to segment the frontal segmentation of instructional videos to achieve the extraction of video feature vectors. Shi X et al. used computer-aided methods and mobile intelligence to optimise the design of physical education teaching, which was effective in improving teaching efficiency and student motivation [18]. In physical education and motion analysis, feature extraction with the help of posture recognition can effectively achieve action recognition, so the study uses human posture recognition algorithm for the design of motion evaluation system to better improve the application of physical education.

3. Design of improved human posture recognition algorithm and research on sports evaluation system. Human posture recognition is an important premise and basic content of the research. First, the research improves the human posture recognition algorithm. With its application in sports, the research uses VGGNet-19 as the feature extractor to capture the posture algorithm, and introduces the concepts of joint angle and motion similarity to carry out limb angle information and geometric spatial analysis analysis. Subsequently, starting from the requirements of the sports evaluation system, a sports evaluation system is built based on human posture recognition algorithm and joint angle distance evaluation, in order to better design a evaluation

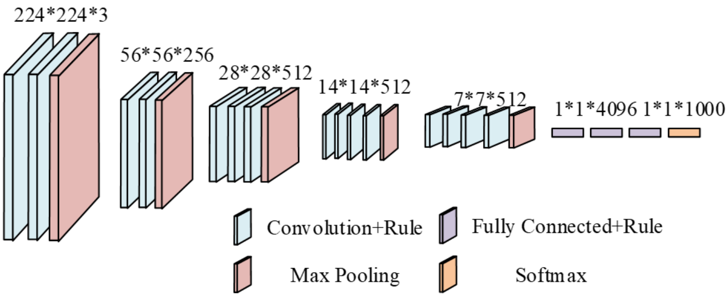


Fig. 3.1: Schematic diagram of VGGNet-19 network structure

system that meets the user's sports needs.

3.1. Application of human posture recognition algorithms in sports design. Conventional tools for human pose recognition are mainly analysed with the help of depth images or wearable device technology, but the costly nature of the research and the limited range of motion make it difficult to show good applicability in pose recognition. For acquiring key data for deep learning, open source software such as OpenCV is good for analysing the pose test module, but the effect of testing key points can be affected by environmental conditions, light sensitivity and other factors [19]. Therefore, the study applies OpenCV software with high robustness to the construction of human pose recognition system, and uses VGGNet-19, which can better adapt to different resolution image data, as the feature extractor. openPose extracts multiple key points from a single image frame simultaneously when performing human body recognition, and applies the affinity field method with real-time and targeting to the two-dimensional pose image of human body to The VGGNet-19 network is a deeper structured convolutional network, and its expansion of the network depth enables better network performance [21]. The VGGNet-19 network can be used to extract the image features and explore their depth of meaning. Figure 3.1 shows the structure of the VGGNet-19 network.

The VGGNet-19 network replaces the three fully-connected layers in the training process with three convolutional operations, making the final fully-convolutional network free from the limitation of fully-connectedness, so it is not limited by the width and height of the input data at the moment of input data.The VGGNet-19 can process input image data with different resolutions in Open Pose human pose recognition, and it mainly focuses on the confidence map feature of the key parts of the human body in the image. The confidence map features of the key parts of the human body are acquired.VGGNet-19 is used as a backbone feature extractor which is responsible for extracting the useful features from the input image.Passing the input image in the pre-trained VGGNet-19, different types of feature maps related to the gesture action can be acquired, which are convolved and downsampled to acquire the key points of the human body. The processed feature maps can generate Heatmap for pose estimation, the feature maps obtained in this processing stage can be lost to improve the convergence performance of the network, and the Heatmap predicted in the previous stage can provide rich spatial information, which plays an important role in the identification of joint points.When the system network performs body part location prediction, it forms a set of vector fields containing a combination of a confidence map and a partial affinity field, which effectively encodes the part association. The OpenPose network is trained using a multi-stage convolutional neural network structure, where the first ten layers of VGGNet-19 data are initialised to generate the input body feature map, and subsequent stages of images are cascaded with affinity fields and confidence map predictions. is shown in Figure 3.2.

In Figure 3.2, the first part of the OpenPose network structure, the network for key point detection first produces a part of the affinity field, and in each subsequent stage, the prediction results it produces will be associated with the fields produced in the first stage and the original graph features to improve the accuracy of its prediction.When key points are detected in the human pose recognition process, the subsequent predictions generated are linked to the affinity field generated in the first stage and the original graph features to improve

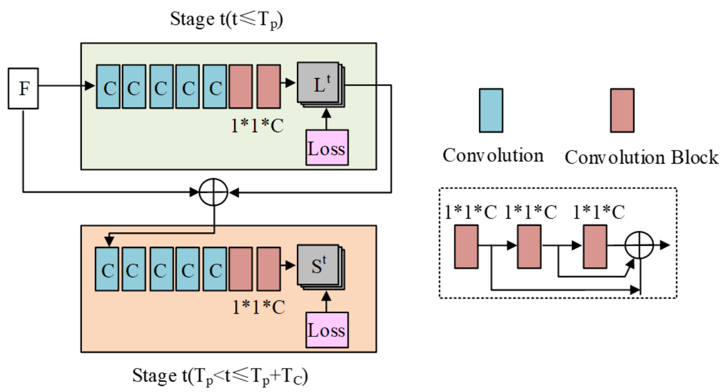


Fig. 3.2: OpenPose Network Structure

their prediction accuracy. The mathematical formulation of the affinity field is given in equation (3.1).

$$L^t = \phi(F, L^{t-1}), \forall 2 \leq t \leq Tp \tag{3.1}$$

In equation (3.1), ϕ represents the convolutional neural network for the prediction phase t, Tp is the total affinity field prediction, Tp is the number of iterations, F is the original graph feature, and ϕ is the set of vector fields for the prediction phase $t-1$. Repeating the prediction phase process requires the prediction of the confidence map, which is mathematically expressed in equation (3.2).

$$\begin{cases} S^{TP} = p^t(F, L^{TP}), \forall t = Tp \\ S^t = p^t(F, L^{TP}, S^{t-1}), \forall Tp < t \leq Tp + TC \end{cases} \tag{3.2}$$

OpenPose pose recognition itself contains occlusion problems and slow speed problems that can interfere with the recognition results. The common ideas for improvement are to reduce the model file by modifying the network model or to increase the number of processors by improving the hardware environment, but these two methods reduce the reliability of the motion evaluation system and consume more costs [22]. Therefore, the study started with the data to be measured and improved the fluency of the system by downsampling the images or data, i.e. setting the width and height in the feature extractor to 640 and 480 respectively, and compressing the images or videos in equal proportions. There are differences in the postures presented by the state changes of the joints during human movement, and the limb pinch features can also show similarities, which can easily lead to wrong judgement of movements. Therefore, the research is based on the limb angle information, with the addition of the centre of gravity vector information and the geometric spatial features of human posture for differential posture feature recognition. The flow of the feature extraction algorithm is shown in Figure 3.3.

In Fig. 3.3, after reviewing the video, detection is performed with the help of OpenPose pose recognition to determine whether there is an action pose, and if there is, then the skeletal point position information is extracted, the skeletal coordinate system is established in the unified coordinate system, the features of limb angle, axis, and limb direction are extracted and fused with the features, and the respective labels are created for the joint feature information of each pose, to complete the acquisition of the human body pose information. The human posture is extracted by first normalising the skeletal point position coordinate data to obtain the original sequence data, then using the human centre of gravity method, the limb angle calculation method and the skeletal point joint coordinate data calculation to obtain the feature vector data, and then fusing the three feature information to obtain the final human posture feature information. Equation (3.3) is the expression formula for the posture feature information.

$$F' = [G, V, O] \tag{3.3}$$

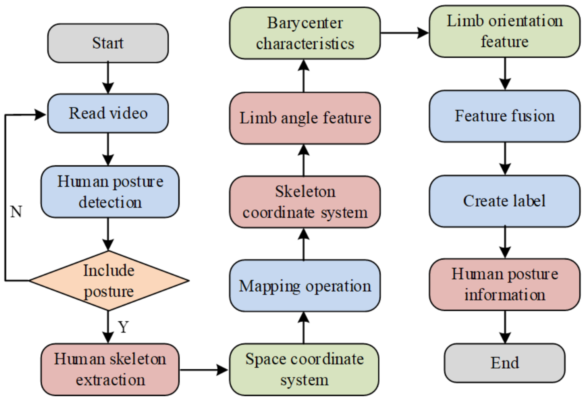


Fig. 3.3: Human pose feature extraction algorithm flow

In equation (3.3), G is the centre of gravity vector angle feature, V is the set of human limb angle features, and O is the set of limb orientation features. The formula for the skeletal point data conversion is shown in equation (3.4).

$$pi1 = pio - p10 = (xi0 - x10, yi0 - y10) = (xi1, yi1) \tag{3.4}$$

In equation (3.4), $pi0 = (xi0, yi0)$ represents the original coordinate data of the i joint point, and $pi1 = (xi1, yi1)$ is the coordinate data after the new coordinates. The moment synthesis method is used to transform the mechanical situation of the human centre of gravity into a combined moment of constant force, and the coordinates of the human centre of gravity are obtained according to the position and weight of each sub-extremity $(\frac{\sum Gi \cdot Xi}{G}, \frac{\sum Gi \cdot Yi}{G})$. The calculation is shown in equation (3.5).

$$\begin{cases} x = \sum ki \cdot Xi \\ y = \sum ki \cdot Yi \end{cases} \tag{3.5}$$

In equation (3.5), ki denotes the link correlation coefficient corresponding to each$i$ limb. When performing the calculation of limb angle pinch angles, the study was carried out with the vector inner product to obtain equation (3.6).

$$\theta = \arccos\left(\frac{\vec{G} \cdot \vec{M}}{\mid \vec{G} \mid \cdot \mid \vec{M} \mid}\right) \tag{3.6}$$

In equation (3.6), $\vec{G}$ and $\vec{M}$ represent the centre of gravity vector and the spine vector respectively, andθ represents the angle between the two. The principle is to operate on the direction vector with the help of the positive tangent function to obtain the radian information.

3.2. Design of recognition algorithm and evaluation system based on joint angle and movement similarity. The algorithm based on human pose recognition only locates the human joint points, but further extraction of the joint point coordinates is crucial. At the same time, due to the uncertainty of the human body in motion and the differences in its movement angles, the results of the two-dimensional action recognition images are also different and need to be analysed with the help of certain action description rules. The study introduces joint angle indicators and movement similarity for evaluation and analysis. The joint angle is the angle formed by the joint part adjacent to the front and back joints, which can be achieved by means of the cosine of the three-point coordinates, while the action similarity is used to identify the action by rule, which also enables the identification of continuous action sequences[23]. Action similarity is the core of

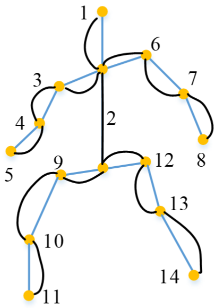


Fig. 3.4: Schematic diagram of human skeleton model labeling

describing action rules, which can be used to calculate the "distance" between two actions to identify individual actions, and can also be used to find out the "standard action" in a continuous action sequence. The calculation of the "distance" is still achieved by the joint angle data of the two actions, and the introduction of joint angle and motion similarity can be used for the evaluation of the action in human posture recognition to assist in judging the feature data extracted from the recognition image. The human posture recognition technology extracts the joints of the characters from the video or image containing the key actions, and calculates the respective joint angles, which are sorted and saved in the database according to the sequence of the actions, such as Action 1, Action 2, Action 3.... etc. Subsequently, the joint angle data of all the actions in the video are extracted and filtered with the joint angle data of the actions tested in the standard action database, which can be used for action evaluation. Setting the joint angles of the action to be measured and the template action to *Angle*, and *SAngle* respectively then the distance between the two vectors can be solved with the help of the Euclidean distance, whose mathematical expression is shown in equation (3.7).

$$\begin{aligned} D = ((SAngle1 - Angle1)^2 &+ (SAngle2 - Angle2)^2 + (SAngle3 - Angle3)^2 \\ &+ (SAngle4 - Angle4)^2 + (SAngle5 - Angle5)^2 + (SAngle6 - Angle6)^2 \\ &+ (SAngle7 - Angle7)^2 + (SAngle8 - Angle8)^2)^{0.5} \end{aligned} \tag{3.7}$$

The eight joint points are selected in equation (3.7). The smaller the Euclidean distance, the more similar the movements are and the better the joint angles are identified. Figure 3.4 shows a diagram of the human skeleton model markings.

The research was then based on the improved stance recognition algorithm proposed by the study to design a sports evaluation system a sports assistance evaluation system to help trainers to analyse their own sports state and process, and then improve their own deficiencies, so the research is based on OpenPose stance recognition and joint angle distance action evaluation, the design of the sports system, and in the process of system development and testing with a school secondary school students sports action as a test The object of the system development and testing is the sports movement of secondary school students. The functional design of the system is shown in Figure 3.5.

In the functional requirements design, the system establishes a standard action database based on key actions, so the evaluation focuses on the analysis of joint angle differences. Firstly the user needs to access the system window with the help of a password and user name, secondly the key movement images are captured in the movement database module and the system automatically implements the identification and saving of joint angles for key movements. Subsequently, in the assisted teaching module design, the user can practice the movements according to their situation and pause the exercises when the user's movements have a good resemblance to the movements captured by the system. The user can also analyse their own learning in the general assessment module, where the system will analyse the exercise work against key movements in the standard movement database for movement frame analysis, presented as Euclidean distance of the movement and joint angle data. The OpenCV 4.1.0 open source computer vision library enables the acquisition, loading, saving and transposition of images and videos. It has good image data processing capabilities as well as

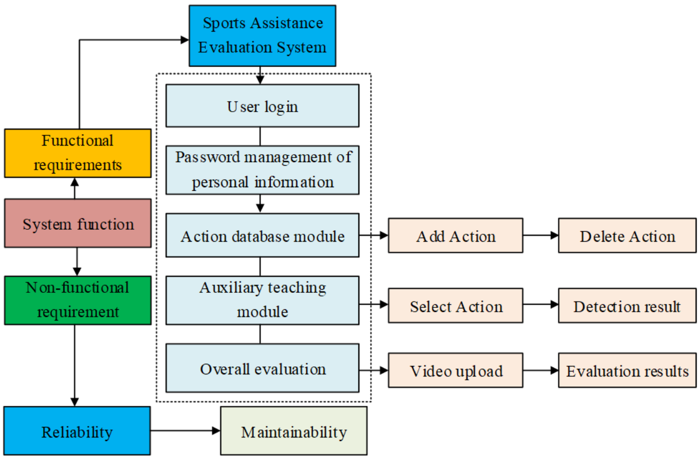
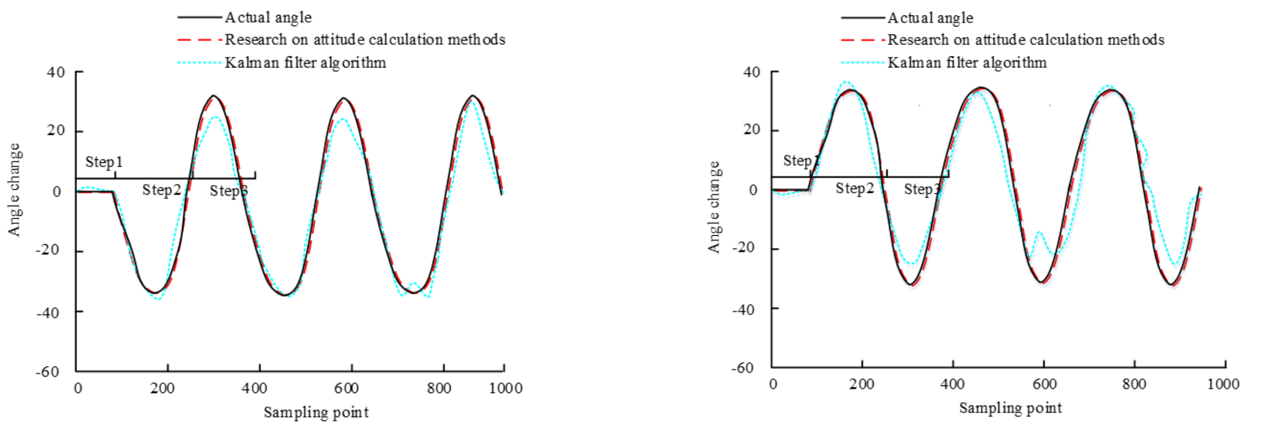


Fig. 3.5: Overall Design of System Functions

capture capabilities. In the data pre-processing part, OpenCV normalises the resolution of the input annoying image video to 480*360 and acquires the coordinates of the human skeletal points in the video. The obtained skeletal point coordinates are scaled isometrically to account for the effect of resolution changes on the skeletal information. In the feature extraction and pose matching section, the user's key movements are identified and similarity is calculated, thus enabling the user's movements to be scored to help them learn to correct their own movements.

4. Analysis of the results of sports evaluation applications with improved pose recognition algorithms. When designing the standard movement database, the collected movements are the key movements in sports, and the selection criteria and number of movements can be decided according to the norms of movement design and specific situations. The four pairs of movements that are prone to misjudgment in sports movement teaching are collected for analysis, i.e. leg raise, sideways, lift and lunge, and the video frames of each movement are taken as the collected data, which are captured by a camera shooting at 30 frames per second, obtaining the coordinates of the skeletal point data, marking the filenames, and distinguishing the movement data with the interference of the adjacent frames with the class sequence number. During the experiment, we design the relevant environment parameters, namely, the operating system is Windows10 64bit, the memory is DDR4 2400MHz 8GB, the CPU and GPU are Intel(R) Core(TM) i5-8300H 2.30GHz and NVIDIA GeForce GTX1050Ti 4G, and the software platforms include Qt5.9.0, VisualCon, and Qt4.1.0, and VisualCon. .0, Visual Studio 2015 and OpenCV.The resolution of the video file is 480p, and the frame rate is 30fps.During the experimental data acquisition process, the distance between the experimenter and the camera is designed to be 2-3 metres.The software platform is built in the Visual Studio 2015 environment, and the OpenCV computer vision inventory and C++ development are selected as the basic class library, which can process the involved data types as well as text information. Subsequently, the collected data were randomly divided into template set and test set according to the ratio of 6:4, and the similarity of pose calculation was used as the basis of judgement, and the threshold was set to 0.9 for the output of results.For the comparison of experimental results, the study compares the proposed improved gesture recognition algorithms, whose main evaluation metrics include Accuracy, Recall, and Teaching Evaluation Results, among others. Among them, Accuracy and Recall are commonly used metrics to evaluate the performance of classification models. Accuracy, defined as the number of samples correctly predicted divided by the total number of samples, measures the model's predictive accuracy across all samples and is a commonly used evaluation metric. Recall is defined as the number of positive samples correctly predicted by the model divided by the total number of true positive samples, which measures the model's ability to identify positive samples, and is an indicator for evaluating the sensitivity of the model and its ability to find true positive samples, and a higher recall indicates that the model



(a) Posture recognition results under a single action

(b) Posture recognition results under repeated actions

Fig. 4.1: Action posture curves of two algorithms

is better able to find positive samples. Accuracy emphasises the overall accuracy of the model's predictions, with higher values indicating that the model's predictions are more consistent with the true results. Mean Squared Error (MSE) and F1 value are mostly used to evaluate the performance of different types of tasks, MS is defined as the average of the squares of the difference between the predicted and true values, the smaller the MSE, the smaller the difference between the predicted results of the model and the true values, i.e., the better the model is fitted.The F1 value is a measure that combines both the accuracy and the recall, which combines the effects of accuracy and recall, especially more effective in the case of unbalanced categories.The value of F1 value ranges from 0 to 1, and the closer it is to 1 means the better the results predicted by the model. The main content of the study is the human posture recognition algorithm, so the analysis of the recognition of the posture and its accuracy with the standard movement, and the recall of the comparison algorithm can effectively assess the sensitivity of the algorithm to process the sample data. As for the evaluation of teaching movement, the study analyses the effectiveness of teaching with satisfaction, which can effectively analyse the practical ability of the application of the algorithm [26, 25, 24].

The pose solution method used for the study was compared with the pose Kalman filter algorithm for the analysis of the solution results and a simple kick action was used for the pose analysis. This leg lifting action can be divided into three steps of lift-kick-out-retract, and the action pose curves of both algorithms are obtained, as shown in Figure 4.1.

In Figure 4.1, the identification fit between the stance curve and the actual curve under the Kalman filter algorithm is above 90% under single action training, but it has significant nodal fluctuations at sample points 300, 600 and 750, with a maximum deviation rate of 4.17% from the extraction of the algorithm proposed in the study. The magnitude of the deviation of the posture curve between the two compared algorithms was extended to a maximum of 6.38% under repeated action testing, followed by joint angle calculation with the stance of standing on both feet and arms open, which is shown in Figure 4.2.

In Figure 4.2, the overall deviation of the proposed pose recognition algorithm from the real curve for joint point angle analysis does not exceed 2%. However, the Kalman filtering algorithm deviates from the real curve to varying degrees from one joint point to another. These results show that the proposed algorithm is able to recognise human movements well. The matching accuracy of the different algorithmic models for human pose recognition was then analysed and the comparison results are shown in Figure 8.

In Figure 4.3, the accuracy of the proposed pose recognition model in matching broad and detailed movements showed a more significant difference in accuracy with the Dynamic Time Warping (DTW) model and the Convolutional Neural Network (CNN) model. The improved pose recognition model achieved 94.8% and

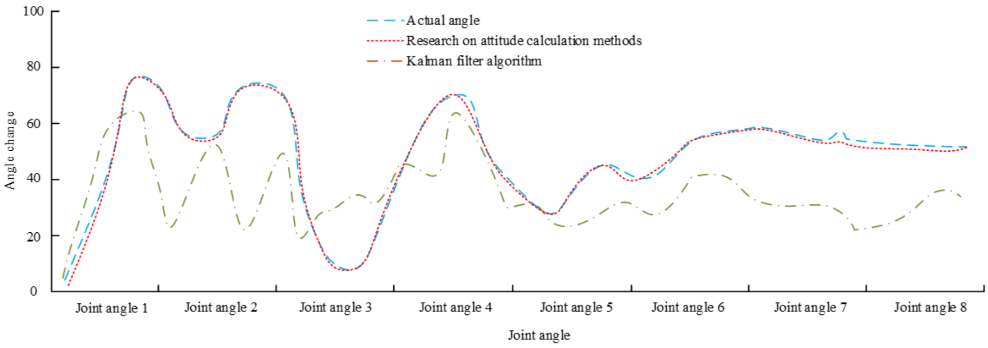


Fig. 4.2: Recognition Results of Two Algorithms under Joint Angle

93.4% action recognition accuracy on both data sets, with the highest matching accuracy (98.65%) for the lunge action. was less effective, with matching rates of 88.7% and 89.2% in datasets A and B, respectively, with a difference margin of 6.1% and 4.2% compared to the pose algorithm proposed in the study. The recall exhibited by the three algorithms was then analysed and the results are shown in Figure 4.3.

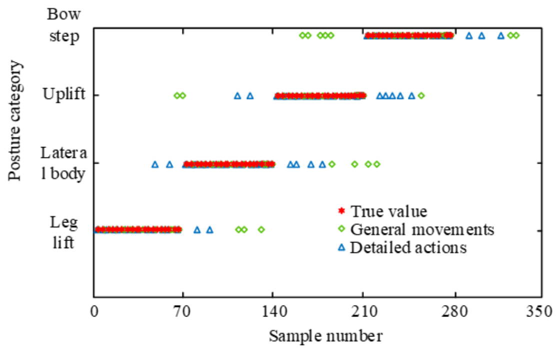
In Figure 4.4, the recall of the improved pose recognition algorithm model stays within the interval of [0.60, 0.67] and [0.68, 0.74] respectively during the training process on both datasets, and its overall recall changes at a more stable rate. The aforementioned findings demonstrate that the enhanced gesture recognition algorithm can successfully distinguish between positive and negative actions, and that the gesture actions are retrieved more effectively. The errors of the three algorithms in performing human action recognition are shown in Figure 4.5.

In Figure 4.5, the improved pose recognition algorithm's recognition error is shown to be substantially lower than that of the other two examined methods. Its maximum error value is 0.010, and it exhibits less overall variance. The maximum recognition error values for the DTW and CNN algorithms are 0.014 and 0.017, which are 0.004 and 0.007 higher than the algorithms proposed in the study, and the error curves for these two algorithms are less occurring in a numerical continuum. The results of the different algorithms for pose recognition were subsequently analysed with the help of ablation experiments, the results of which are shown in Fig. 4.6.

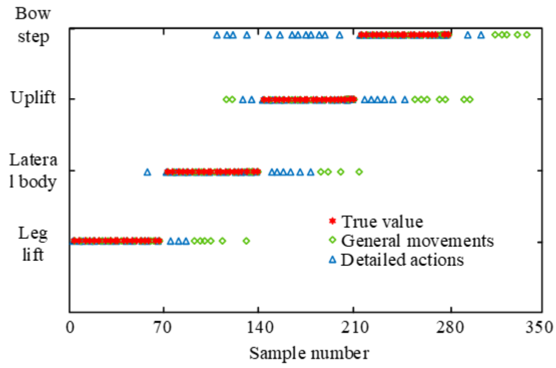
In Fig. 4.6, the MAE error value (0.1208) exhibited by the study's proposed algorithm is smaller than the DTW model (0.1742) and the CNN model (0.1503), and its F1 value (0.6923) is larger than that of the DTW model (0.6212) and the HRNet-w48 model (0.5849). The results of the teaching application of the system with this algorithm were analysed in terms of the users of the recognition algorithm in the assessment of physical education, which mainly reflected the effect of the teaching ratings and the satisfaction of the students' feedback, as shown in Figure 4.7.

In Figure 4.7, the improved posture recognition algorithm proposed in the study resulted in a mean score of 86 for the students in PE, followed by the better performing DTW and CNN models, which corresponded to mean grade scores of 76 and 68. The student satisfaction results showed that the improved posture recognition algorithm achieved 92% satisfaction, significantly higher than the DTW and CNN models with 78% and 64% satisfaction. These results show that the improved posture recognition can better assist the teaching of physical education and effectively improve the students' performance in physical education.

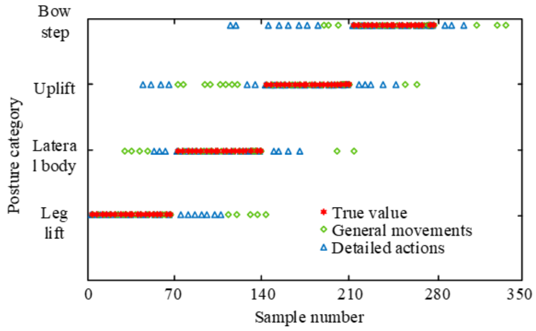
5. Conclusion. The application of human posture recognition algorithms to sports assessment systems can better capture and recognise sports movements, and effectively avoid the disadvantages of traditional training methods of data recording. The study proposes a stance recognition algorithm based on joint angle and movement similarity to design a sports assessment system for physical education. The results show that the stance curve of the kicking action obtained by the proposed stance solution method has a higher similarity to the actual situation, much higher than the comparative algorithm Kalman filter algorithm, and the maximum



(a) Research on Proposed ALgorithm

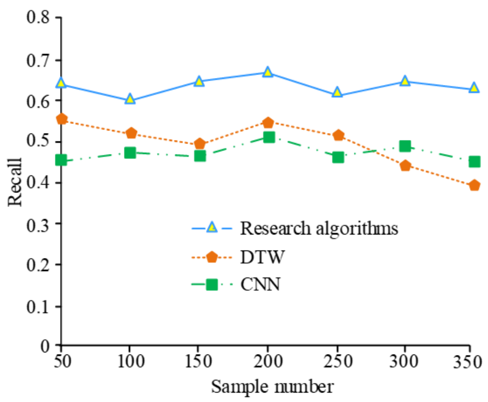


(b) DTW Model

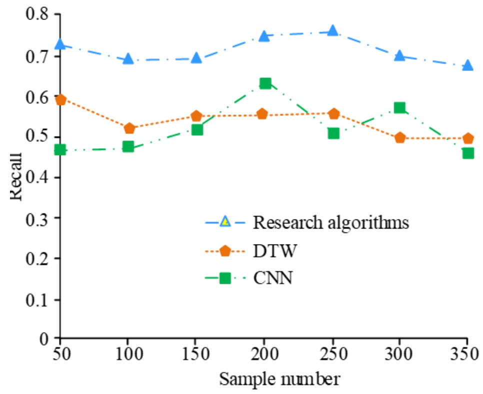


(c) CNN Model

Fig. 4.3: Comparison of matching accuracy under different algorithm models



(a) General Movement set



(b) Detailed Movement set

Fig. 4.4: Comparison of matching recall under different algorithm models

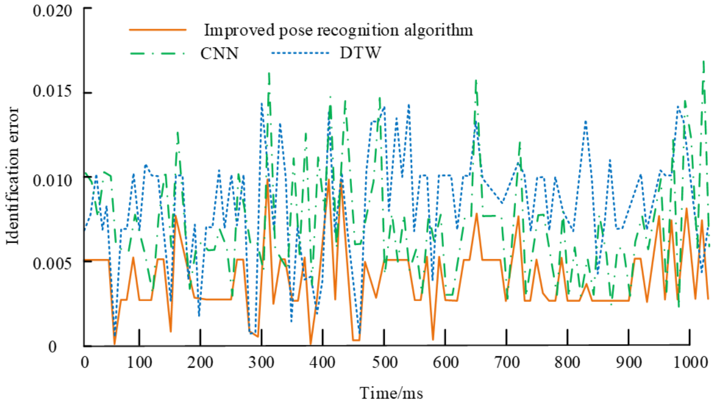


Fig. 4.5: Identification error of three models

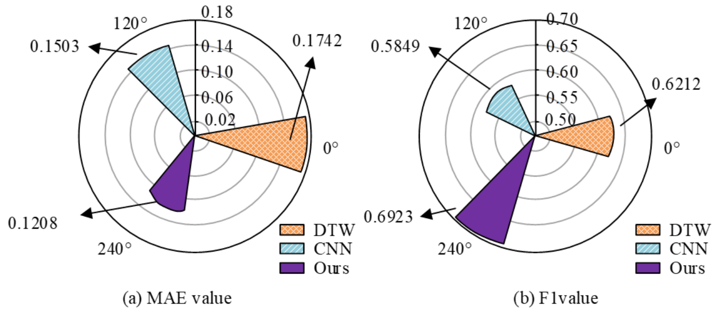
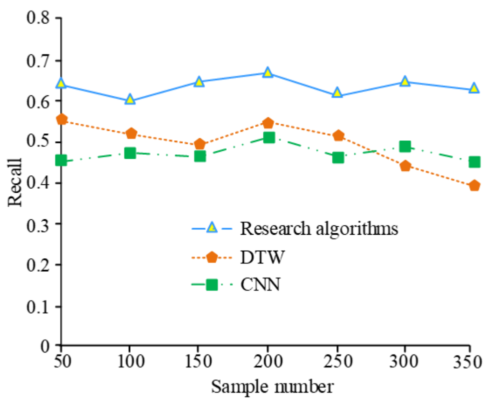
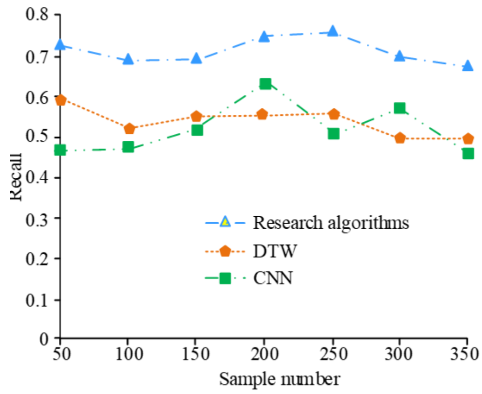


Fig. 4.6: Ablation results of different algorithms



(a) Evaluation scores of different algorithms in physical education teaching



(b) Student satisfaction with the effectiveness of physical education teaching under different algorithms

Fig. 4.7: Practical Application Results of Sports Evaluation System

deviation rate between them reaches 4.17%. The improved pose recognition algorithm has a deviation of less than 2% in the joint angle error, and the accuracy of matching the general and detailed movements is 94.8% and 93.4%, which is much higher than the 91.1% and 88.5% of the DTW model and 88.7% and 89.2% of the CNN model. And the recall of the improved pose recognition algorithm model remained within the interval of [0.60, 0.67] and [0.68, 0.74] respectively, which is higher than the range of [0.39, 0.58] and [0.48, 0.60] of the DTW model, and the overall discrimination of action recognition is better, and the maximum error value of human action recognition 0.0010 is smaller than that of the DTW algorithm and CNN algorithm The sports assessment system designed with the improved posture recognition algorithm was able to improve the students' professional rating results (86 points) and satisfaction (92%), better than the 76 and 78%, 68 and 64% scores of the DTW and CNN models. This sports assessment system is a good training aid, and consideration of upgrading the hardware configuration and adding factors influencing the assessment of movement standards is one of the elements that need to be further investigated in future studies.

Fundings. The research is supported by 2021 Jiangsu University Philosophy and Social Science Research Project, Research on the Ways to Improve the Efficiency of Physical Education in Colleges and Universities from the Perspective of Curriculum Ideology and Politics (2021SJA1144).

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Edited by: Mudasir Mohd
Special issue on: Scalable Computing in Online and Blended Learning Environments: Challenges and Solutions
Received: Nov 9, 2023
Accepted: Mar 4, 2024