Jiang X et al. (2024) EVALUATION OF ATHLETE PERFORMANCE AND RECOVERY IN AN INTELLIGENT SPORTS ENVIRONMENT. Revista Internacional de Medicina y Ciencias de la Actividad Física y el Deporte vol. 24 (95) pp. 382-403.
DOI: https://doi.org/10.15366/rimcafd2024.95.024

ORIGINAL

EVALUATION OF ATHLETE PERFORMANCE AND RECOVERY IN AN INTELLIGENT SPORTS ENVIRONMENT

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Recibido 19 de Junio de 2023 **Received** June 19, 2023
Aceptado 20 de Febrero de 2024 **Accepted** February 20, 2024

ABSTRACT

Artificial intelligence technology as an important force driving the new round of scientific and technological revolution and industrial change, Open Pose Skeletal Tracking is a kind of algorithm based on computer vision technology, which plays an important role in quantitative sports and whole-body posture detection. In this paper, we constructed an intelligent system based on Open Pose bone tracking technology to assist aerobics training, and determined the corresponding experimental indexes, and carried out an 8-week experimental intervention on 50 athletes through the experimental method. The study concludes that artificial intelligence can be an empowering aid for performance-oriented and differentiated training-based athletic training, which is currently faced with the obstacles of insufficient infrastructure, privacy leakage of athletes, and incomplete talent protection mechanism.

KEYWORDS: Intelligent Sports Environments; Recovery; Athlete Performance

1. INTRODUCTION

The rapid development of artificial intelligence technology has had a huge impact on almost all areas of our lives. The field of athletic training is no exception; as modern smart technologies are disrupting the traditional training paradigm to maximize athletes' competitive abilities. Smart Sports Training (SST) utilizes wearables, sensors, gyroscopes, and IoT devices and related smart data analytics tools to reduce coaches' workload while improving athletes' training performance. Starting from the basic concept of AI-enabled sports training, this study explores the practical applications, practical dilemmas and optimization paths of AI-enabled sports training, with a view to providing useful reference and theoretical support for China's sports training career in the context of the era of artificial intelligence.

Open Pose is an open source library researched and developed by the Perceptual Computing Laboratory at Carnegie Mellon University, USA, which can support pose estimation of multiple parts of the human body, face, fingers, and other parts of the human body in both single and multi-person situations; it is an open source library that utilizes Open CV and Caffe and is written in C++ for multi-threaded, multi-objective human skeleton key-point detection (Hara & Chellappa, 2017).

Open Pose adopts a bottom-up human skeletal key point detection method with strong practicality and good robustness, and is the first real-time pose recognition model based on deep learning. The Open Pose algorithm, in order to connect the points together quickly, proposes the concept of Part Affinity Fields (PAFs) for human key points to realize fast joint point connection, which has gained wide attention. The method uses PAFs (Part Affinity Fields) to associate body parts in an image with their human counterparts. The architecture is inherited from CPM and the accuracy of the model is not affected by changes in the number of people present in the image. It can perform pose recognition in real time, which is worth investigating for many real-world application scenarios. The software is copyrighted to Carnegie Mellon University, and the CMU AI program, launched in June 2017 to advance AI research and education, states that anyone and any institution can use it to build their own skeletal joint tracking systems as long as they are not involved in commercial use.

Figure 1: Results of Open pose detecting joint points of human body

Open Pose can detect the joints of the human skeleton in images in both single- and multi-person visual scenes. The actual test results of Open Pose estimation are shown in Figure 1.

2. Related works

The main types of equipment for intelligent assisted practice are: wearable devices, virtual reality technology, sensors, and human posture recognition technology. In wearable devices, the main application is to detect the physical and physiological responses of athletes during training and competition, which can be extracted more easily and quickly from the physical and physiological responses of those involved in the practice. P. Li et al, measured the physical responses and wearable heart rate detector by using a global positioning system device operating at a sampling frequency of 10 Hz in conjunction with a 1000 Hz tri-axial accelerometer applied to the soccer, volleyball and basketball in a college population (P. Li et al., 2021). In virtual reality technology, a training plan is developed, the needs and data of each practitioner are simulated, the environment is virtualized and different opponents are set up for the practitioners to experience through VR technology, and finally, the technical style and athletic performance of the practitioners are analyzed by obtaining these needs and data. The application of virtual reality technology in sports is mainly to establish a virtual sports scene and ideal environment, so as to increase the dialectical materialism that the occurrence and development of anything is a process, the development process of human society is bound to go through the process of natural history from fully developed, to man-made natural history, and then to man-made history (Ma, 2010). Students' interest in learning and enhancement of practitioners' learning (Zhou, 2021). The use of sensors in fencing and taekwondo sports is well established with pressure sensing guards, metal sensors and scoring systems. In fencing sport using a modern computer vision based scoring system for fencing competition referee assistance, respectively wired scoring and wireless scoring system (Athow & Mc Gough, 2021).

Human pose recognition is mainly done by collecting various physical information generated during human movement. For example, Open Pose based on convolutional neural network and supervised learning and caffe as a framework to develop a resource library, can realize the human body movement, facial expression, skeletal joint movement and other gesture estimation, applicable to single and multiple people, with excellent and other robustness (Cao, Simon, Wei, & Sheikh, 2017). Jun Yang et al. developed a monocular image recognition comparison guidance system using Open Pose technology (Yang, Zhang, & Zhang, 2021). Xuemei Chen established a golf swing based assisted training system based on the two-dimensional posture extracted by Open Pose and utilized the parallax principle to recover the three-dimensional posture (Chen, 2018).

Song and Fan applied 3D multitier to recognize and estimate human postures on basketball sports dataset (Song & Fan, 2021). He and Li used Kinect to obtain the spatial coordinates of human joints, and analyzed the posture recognition by calculating the angles and defining the body pose library through the highlight method, which can be applied to monitoring and analyzing the pull-ups for students' physical education (He & Li, 2020). And Luo Dawei et al. researched the human posture recognition method from multiple dimensions, and elaborated on the difficulties and difficulties as well as the development trend (Luo, Zheng, & Jennifer, 2018).

In terms of human posture comparison, Wang Jianbo and Qiu Kai et al. established an artificial intelligence coaching system, AI Coach, based on deep vision tracking through anomaly detection and performance rating (Wang, Qiu, Peng, Fu, & Zhu, 2019). Kim T T et al. proposed an analysis method using vision-based posture estimation in order to find the key point, which evaluates and quantifies the golfer's golf swing action pairs and outputs the evaluation results through their key moments (Kim, Zohdy, & Barker, 2020). Hu Jianlang et al. researched and realized a three-dimensional posture evaluation method based on a binocular zoom servo system combined with an attention unit tracking mechanism to address the problems of non-standard and unsupervised motion postures (Jianlang, Yarong, & Chi).

Coriander Wang designed and trained a posture assessment model for badminton players based on the concepts of similarity and local evaluation (Daphne, 2020). Ruimin Li designed and implemented an action classification method based on handmade features and other action classification methods and a high-precision action detection method based on the directions of action classification, action detection and action assessment, respectively (R. Li, 2020).

Sheng Li et al. designed and realized a standing long jump action intelligent evaluation system based on human posture recognition technology to address the problems of action irregularities and unequal quantification of performance in standing long jump teaching scenarios (S. LI et al., 2022). It has also been investigated that Media Pipe Pose is an ML solution for high-fidelity body pose tracking, utilizing Blaze Pose's research to infer 33 3D skeletal key points and background segmentation masks for the entire body from RGB video frames, such that it also provides support for the MLKit pose detection API. Current state-of-the-art methods rely heavily on powerful desktop environments for inference and can achieve real-time performance on most modern cell phones, desktop or laptop computers, python and even the web.

With the development of sports training practice and the further deepening of people's understanding of the connotation and extension of sports training, the traditional methods of sports training analysis can no longer meet the current needs of people for sports training. In sports training, the emergence of sports artificial intelligence breaks the traditional analysis mode, enabling researchers to have higher efficiency in the field of technical and tactical analysis and accelerating the scientific process of sports training.

3. Intelligent movement environment construction

3.1 Open Pose Skeletal Tracking Smart Motion Environment Overall Design

The system builds up an information base of standard movements of aerobics by extracting the movement features in the standard aerobics videos, then captures the video data of athletes' aerobics practice in aerobics classrooms using cell phones, video cameras, etc., and then carries out postural estimation of a certain key point of the human body in the video, and evaluates the degree of participation of the key point of the human skeleton in the process of completing the various phases of the technical movements by matching it with the key movements in the standard information base, which serves as a criterion of evaluation, in order to help the athletes to discriminate the norms of the movements in the practice of aerobics and to provide guidance to the athletes.

The system will be based on the analysis of system requirements, combined with related technologies, the overall system design of the skeletal positioning motion analysis system. The system includes action data acquisition module, standard action pose setting module, action pose skeletal motion localization analysis module, and intelligent evaluation feedback module. Aerobics action data acquisition module is used to obtain the standard action posture image sequence from the standard video is created by Tian Kun, Hao Eucalyptus Ying by the Guangzhou Institute of Physical Education and Guangdong University of Foreign Studies, Lu Lu, He Xue and other demonstrations of Guangdong Province, Guangdong Province, students of the required routines - a level of aerobics routines video to get to the image sequence of the action video.

The standard action pose setting module conducts target detection model training and pose recognition based on the standard pose image sequences to train a standard motion pose detection model and form a 2D model of each action pose standard. The action pose skeleton localization analysis module uses the student's action pose detection model to detect each frame of the test image, identifies similar action poses through Open Pose, and analyzes the skeleton localization after obtaining the information of the key bone nodes. The Intelligent Movement Evaluation and Feedback Module is used to display the results of the Skeletal Localization Analysis Module, including scoring the movement poses and giving suggestions for correcting the movement poses. The overall architecture is shown in Figure 2.

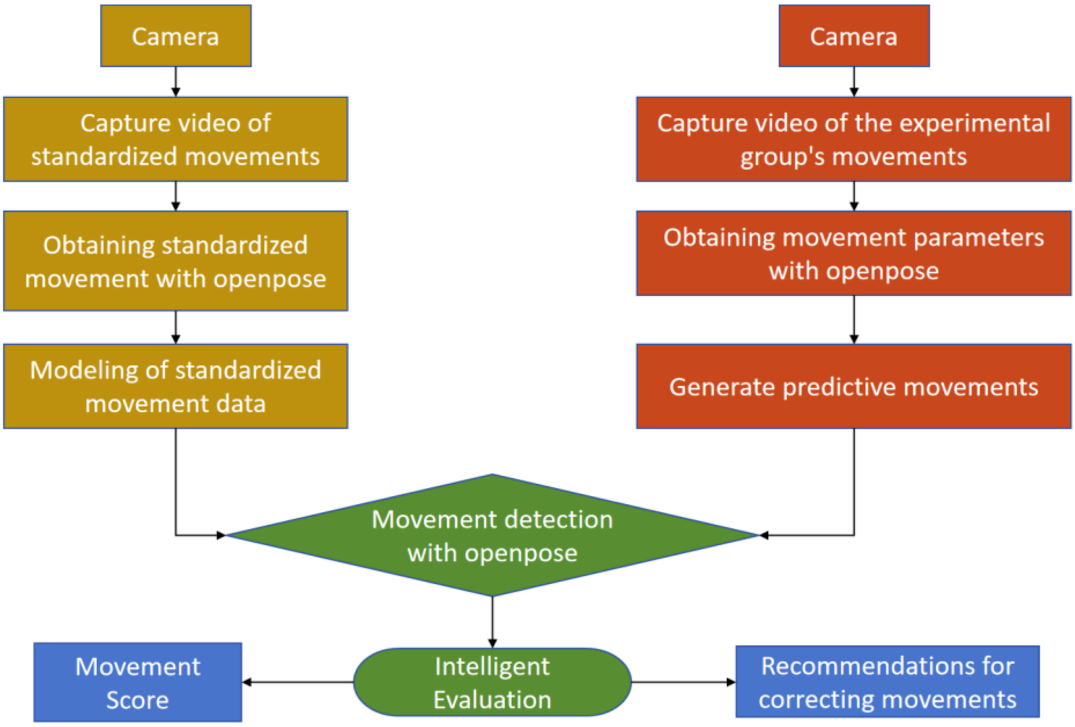

Figure 2: System Framework Diagram

3.2 Motion Data Acquisition Module

Firstly, using a cell phone or with a video camera directly to the practitioner to be tested aerobics action to shoot, which, aerobics program in accordance with the following Figure 3 way to arrange, the camera will be placed in front of the test area, from the test area of about 4 meters, the test area should be the entire area of the camera acquisition, preferably for the closed area without interference, if necessary, according to the action of the mobile line to follow the left and right to move, in order to facilitate the camera to focus and acquisition, preservation.

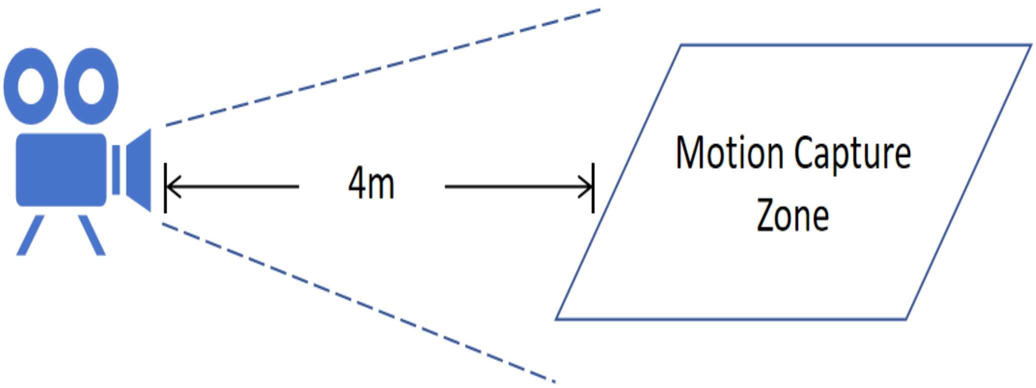

Figure 3: Schematic diagram of video capture of aerobics movements

The relevant information is acquired according to the demand; then in the information acquisition module, it is able to acquire key frames according to the standard video, and finally the standard image sequence is saved to the specified folder. Motion Data Acquisition Module, the acquisition of motion data mainly includes two aspects, the acquisition of standard motion pose data and the acquisition of detection action data. There are two ways to acquire the standardized motion pose data, which are extracting the key frames of the standardized motion poses from the standardized teaching video and directly using the images containing the related standardized motion poses. Images containing relevant standard motions can be directly produced as a dataset, but keyframe extraction is required when processing standard teaching videos.

There are various methods for extracting key frames, and there are differences in the results that can be achieved by using different key frame extraction algorithms. The key frame extraction algorithm based on the inter-frame difference method outputs as key frames by comparing the video frames with the largest gap between two neighboring frames in the video image sequence. There is a certain degree of subjectivity in extracting key frames from standard teaching videos. After comparing various key frame extraction algorithms and combining the rhythmic characteristics of standard teaching videos, the system uses the method of obtaining video frames at equal time intervals of OpenCV standard videos to obtain a standard sequence of motion pose images. As shown in the Figure 4,5.

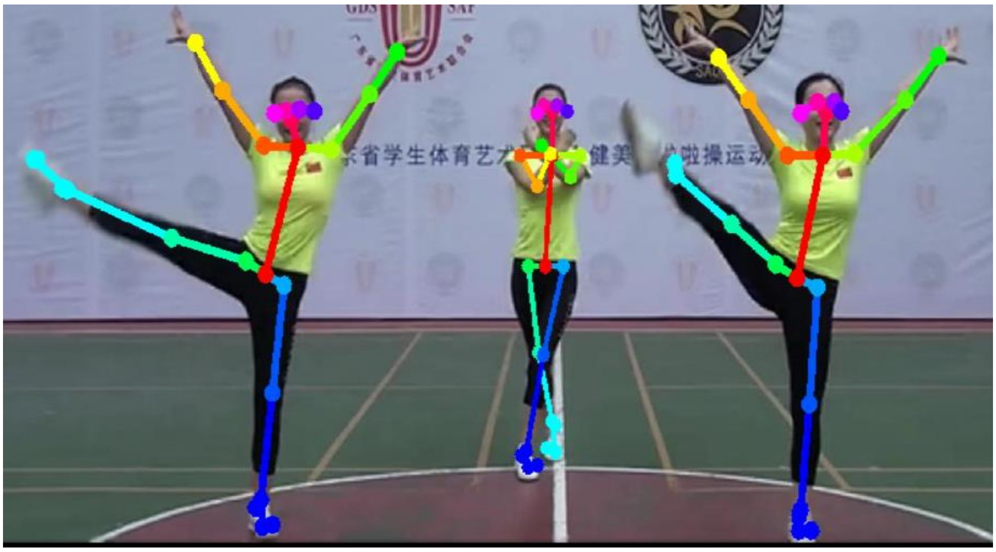

Figure 4: Schematic diagram of the skeleton of the standard movements of aerobics level 1 routines

The test images are acquired by detecting each frame of the video using Open CV, recognizing the pose estimation of the images where motion poses are detected, processing them to form a 2D model of the human body, and then analyzing them with the standard 2D model of the human body for skeleton localization, and returning the results of the analysis.

3.3 Aerobics Movement Posture Standard Setting Module

The author selected by Tian Kun, Hao Eucalyptus Ying created by the Guangzhou Institute of Physical Education and Guangdong University of Foreign Studies, Lu Lu, He Xue and other demonstrations of the Guangdong Province, the students of the required routines - level 1 aerobics routines movements, the standard action setting module using posture assessment algorithms and key frames of the action feature extraction and other means to build a first-level aerobics standard technical action data information base. The core part is divided into the construction of the two-dimensional model of the standard action data information base for the setting of relevant action postures.

The main function of the standard setting module is to obtain the sequence information of human key points in the standard video. It obtains multiple videos of aerobics level 1 standard movements through the standard movements of the movement teaching videos demonstrated by Lu Lu, He Xue, etc., and then analyzes the captured videos frame by frame, and uses the Open Pose algorithm to estimate the key point positions of the human body objects in the process of executing the technical movements, and outputs the human body key point sequences of all video frames in the sequence of the video timestamps. The human body key point sequence for all video frames is output using the video timestamps as a sequence. As shown in Figure 5, the sequences of human skeletal key points for each combination of aerobics level 1 movements are shown.

Figure 5: Aerobics Level 1 Routine Athlete Movement Skeletal Schematics

The setting of relevant action poses is mainly to train the model for detecting standard motion poses. The system refers to the Yolov5 deep learning framework to build the model for detecting standardized motion poses. The main steps include labeling the image sequences of standard motion poses, and then dividing the labeled image sequences according to the ratio of 8:2 between the training set and the test set, and putting them into the network model for training, so as to get the model for detecting standard motion poses.

In data annotation, we need to obtain the label file that needs to be recognized by Yolov5 framework, which includes the following parameters: the category id of the action, the X coordinate/total width of the target center point/total width of the image, the Y coordinate/total height of the target center point/total height of the image, the relative width of the target frame, and the relative height of the target frame. The purpose of plotting the changes of the coordinate values of the key points of the human skeleton is to facilitate the observation of the salient features and changes of the key points of the human skeleton in the process of aerobics practice. Taking the data of a certain part of the human key point sequence of aerobics movement practice as an example, the change of the X value of the coordinates of the key points of the human skeleton during aerobics practice is plotted as shown in Figure 6.

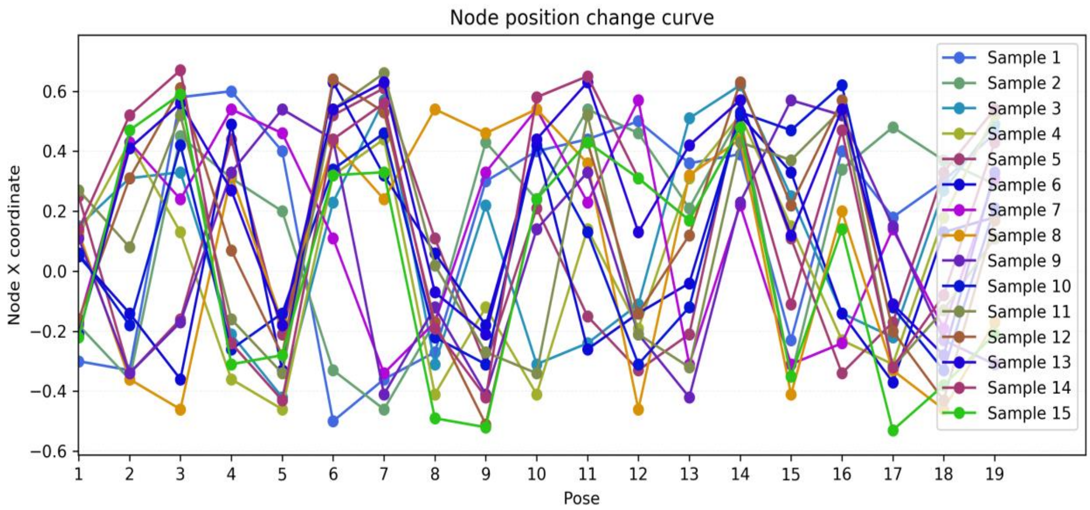

Figure 6: Variation of X-value of coordinates of key points of bones of selected actions

The data annotation tool is able to label the data set to form a txt label file with the above information, and the common data set labeling tools are VIA, Label Me, roboflow, etc. The standard tool used in this paper is make sense. The standard tool used in this paper is make sense.

The two-dimensional model of the human body for standardized aerobics poses is used as the main basis for our judgments of the test movements. The two-dimensional model of the human body can be obtained by analyzing the images of the standard aerobics poses, or by directly setting the human body model of the standard poses. In the image analysis of the standard pose, the system uses the main key nodes and the angle characteristics between the main key nodes as the main indexes for judging the movement. The sequence of the key nodes of the human body recognized by

Open Pose is shown in Figure 7:

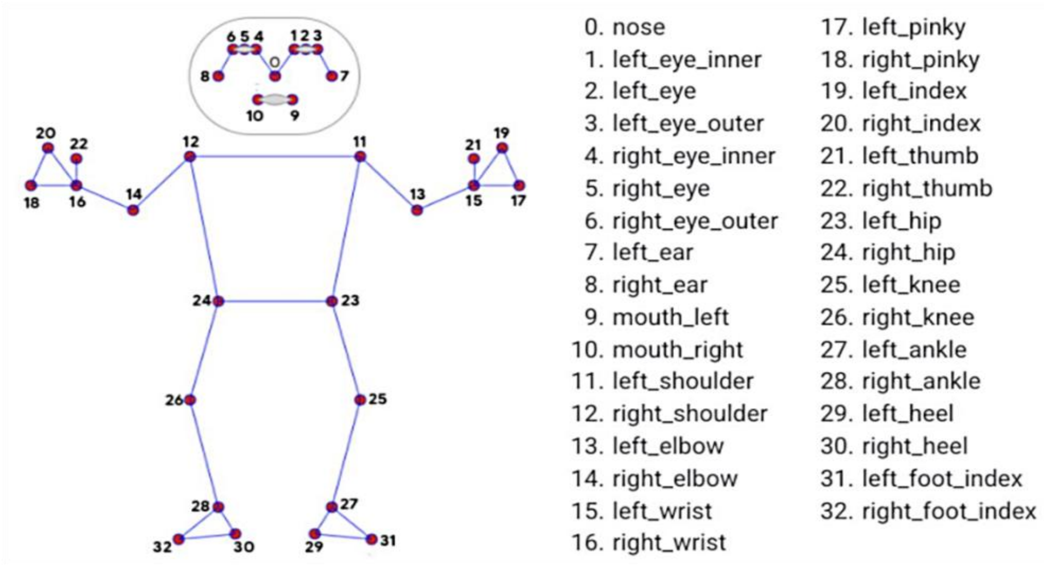

Figure 7: Diagram of human skeletal points

In the key node coordinate characteristics, due to the consideration of different human bodies with different heights and weights and other factors, before comparing the main key nodes, the system will first normalize the relative positions of the main key nodes to achieve a unified standard for comparison. The system normalizes the coordinates of the key nodes by converting the coordinates of the key nodes to the relative position relative to the center point, the coordinates of the center point are (x_i, y_i), there are k key nodes, the coordinate sequence of the key nodes is $L = \{(x_i, y_i): i \in [1, k]\}$, the relative distance of each node coordinate is obtained by using the Euclidean distance and taking the distance with the largest distance X:

$$X = \max_i \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2} \qquad (1)$$

The sequence of relative coordinates of each key node after transformation is $E = \{(x_j, y_j): j \in [1, k]\}$:

$$x_j = \frac{x_i}{X} \qquad (2)$$

$$y_j = \frac{y_i}{X} \qquad (3)$$

In the angular characteristics, 10 angles with large amplitude in the movement posture were selected as indicators for judging, and the angular characteristics are shown in Table 1:

Table 1: Angle Characteristics

ID	SKELETAL NODE SEQUENCE	DESCRIPTION (WITH THE FIRST NODE AS THE VERTEX)
0	0，5，12	Angle between nose, right eye, right shoulder
1	0，2，11	Angle between nose, left eye, left shoulder
2	12，14，16	Angle between right shoulder, right elbow, right hand
3	11，13,15	Left shoulder, left elbow, angle between left hands
4	12，24,26	Right shoulder, right hip, angle between right knees
5	11，23,25	Left shoulder, left hip, angle between left knees
6	12，16,24	Right shoulder, right hand, angle between right hips
7	11，15,13	Left shoulder, left hand, angle between left hip
8	24，26,32	Right hip, right knee, angle between right toes
9	23，15,31	Left hip, left knee, angle between left toes

In this way, a set of two-dimensional models of the human body is designed to form the form for skeletal localization analysis. By comparing the similarity of these features between the two models, it is possible to obtain a prediction of the degree of standardization of the movements, which leads to a score and, by analyzing the data with large differences, to recommendations for corrections.

3.4 Intelligent Assessment Feedback Module

The Intelligent Evaluation Feedback Module is used to provide feedback to the user after analyzing the skeletal positioning motion of a 2D model of the human body in a standard exercise posture and a 2D model of the human body in a predicted exercise posture. For the prediction of athlete exercise videos, the module parses the video and displays in the upper left corner of the video the score of the exercise posture and easy-to-understand corrective suggestions when posture correction is needed. Intelligent evaluation of aerobics movements is not only affected by the motion scene and pixels, but also related to the height and form of the person to be evaluated, as well as the relative position of the camera. The direct use of skeletal point data is not able to establish a common evaluation model, so it is also necessary to convert and standardize the coordinates of the obtained human skeletal points, which is used as a basis to establish the evaluation of aerobics movements. According to the characteristics of aerobics movements, the limbs change a lot during the whole movement, while the core position area is relatively stable. Therefore, the hip center point is used as the reference point to evaluate and analyze the changes of the limbs in the whole movement process. First, the ratio between the X and Y values of the coordinates of the joints of the standard posture and the posture to be evaluated was calculated according to the standing posture of the person in the standard movement, which can eliminate the influence of inconsistencies in the coordinates of the joints of the skeleton of the person to be tested and the disparity of the body shape, so as to carry out the assessment of the posture in a more convenient way. Secondly, after the standardization of the skeletal key point data of the personnel to be tested, the coordinates of the key points of the human body of the athletes' movements to be analyzed in each frame are composed into a sequence of coordinate points, and the correlation coefficient of Pearson's product-moment correlation is used to measure the correlation between the key points of the athlete's aerobics movements and the key points of the standard movements, and the overall similarity between the key frames is calculated in accordance with a certain scaling factor according to the characteristics of the aerobics movements as a measure of the accuracy of the aerobics movements.

The key feature gesture can be composed of two or more skeletal key points connected to the line, and different skeletal key points can be selected and combined in a targeted way according to the characteristics of the research project to be analyzed. Taking the kicking movement of 5 and 6 beats in the third 8-beat of the third section of the first level movement combination of aerobics studied in this paper as an example, we select the following skeletal key points to form the key characteristic postures for analysis according to the characteristics of the program. Through the movement specification guidance of aerobics teaching, we judge the relative position between some nodes, as shown in the figure, we can see that the athletes' movement posture is similar to the standard movement posture of side plank kicking, the predicted scores are 76, 72.5, 73, 70 in order, but in the local posture needs to be corrected, the hands should be upward stretching with the torso into 180 degrees, kicking foot should be The kicking leg should be held upward to 165 degrees.

Figure 8: Analysis of Athlete Movement Scoring Results

As shown in Figure 8 each frame of image in the video is detected, all the detected images are analyzed for skeleton localization movement and displayed on the image, finally the estimated scores of various types of trainers for various types of movement postures are integrated and final scores of the whole set of movements are obtained using summation and averaging, after that the final scores are given by combining the results of evaluation of the changes in the angles of the joints in order to integrate the movement suggestions of the images for each frame and saved as a guidance file.

4. Analysis of Experimental Results of Intelligent Training of Open Pose Skeletal Tracking Technique

4.1 Comparative analysis of athletes' basic physical conditions before the experiment

The Functional Movement Screen (FMS), a method for assessing athletes' movement patterns designed and proposed in the 1990s by American orthopedic training expert Gray Cook and training specialist Lee Burton et al, can easily identify functional limitations and asymmetric development in individuals, and consists of only seven movements. It consists of only seven movements and can be used in a wide range of populations to assess basic movement abilities, including shoulder and hip mobility and core muscle group stability. Functional Movement Screening (FMS) is designed to provide a simpler and quicker understanding of a person's movement quality, and is therefore a comprehensive assessment of the quality of body movement. Along with the popularization of FMS, its assessment is widely used in rehabilitation training and physical training to measure the quality of movement and plays an important role in sports in China. Functional Movement Screening (FMS) is a test of 7 basic movements, which is designed to screen out the weak links in the body's functions that may cause injury and to fully understand the flexibility and coordination of the test subject.

Table 2: Comparative analysis of FMS tests of athletes in experimental and control groups (n=50)

ASSESSMENT INDICATORS	EXPERIMENTAL GROUP (X±S)	CONTROL GROUP (X±S)	T	P
SQUAT	2.01±0.37	2.2±0.41	-0.649	0.512
UPPER STEP OVER THE BAR	1.90±0.53	2.0±0.41	-0.507	0.624
STRAIGHT LUNGE	1.90±0.52	1.89±0.63	0.172	0.714
SHOULDER MOBILITY	2.56±0.77	2.60±0.47	-0.451	0.742
SUPINE LEG RAISE	2.67±0.28	2.24±0.82	1.490	0.166
PUSH-UPS	2.57±0.48	2.7±0.44	-0.508	0.614
TOTAL ASSESSMENT SCORE	1.80±0.66	1.52±0.52	0.600	0.556

Note: *P≤0.05, significant difference; P≤0.01, highly significant difference; P>0.05, no significant difference*.

Functional movement tests were performed on 50 athletes in the experimental and control groups respectively before the experiment, and as can be seen from the analysis of the data in Table 2, there was no clear significant difference in the scores of the FMS functional movement assessment between the two groups of experimental subjects. Using the independent samples t-test for the data obtained, it was found that the p-values of the mean scores of the single functional movement assessment and the total mean scores of the athletes in the experimental group and the control group were greater than 0.05, which indicated that there was no significant difference in the scores of the FMS assessment between the experimental group and the control group before the experiment. The functional training of athletes can reflect the basic physical function level of athletes to a certain extent. According to the results of the data analysis, it can be seen that the experimental group and the control group athletes are at the same level of basic physical function, so the selected experimental group and the control group athletes meet the requirements of the experiment.

4.2 Comparative analysis of motor skill assessment between athletes in the experimental group and the control group after the experiment

Table 3: Comparative analysis of athletes' sets in experimental and control groups (n=50)

GROUP	NUMBER OF PERSONS	X±S	T	P
EXPERIMENTAL GROUP	25	85.52±2.0	6.309	0.000
CONTROL GROUP	25	82.19±1.72		

Note: *P≤0.05, significant difference; P≤0.01, highly significant difference; P>0.05, no significant difference.*

Through the observation and analysis of Table 3 it can be concluded that after comparing the experimental group and the control group athletes in the aerobics level 1 prescribed set movement assessment, it is not difficult to find that, also after 16 hours of experimental teaching, the average value of the experimental group athletes' set movement assessment score is 85.52, and the average value of the control group's set movement assessment score is 82.19, P value is 0.000, less than 0.05. The p-value is 0.000, which is less than 0.05, and there is a significant difference, which is statistically significant. It can be seen through the table that the use of Open Pose bone tracking technology to assist the teaching of aerobics has a very good effect on the mastery of athletes' movement skills, which stems from the fact that the Open Pose bone tracking assisted teaching system has a strong target and can provide real-time feedback and corrective suggestions to the athletes' movement practice, so the athletes of the experimental group can better master the movement learning than those of the control group when conducting the movement assessment. Therefore, the athletes in the experimental group were better able to master the movements than the athletes in the control group during the movement assessment.

4.3 Analysis of stage movement assessment scores of athletes in the experimental group and the control group

In order to further explore the greatest advantage of Open Pose Bone Tracking to assist in teaching, athletes in the experimental group and the control group were assessed in the middle and late stages of the experiment to analyze the changes produced by the experimental intervention, and the results of the analysis are shown in Table 4.

Table 4: Comparative analysis of stage movement assessment of athletes in experimental and control groups (n=50)

EVALUATION STAGE	EXPERIMENTAL GROUP (X±S)	CONTROL GROUP (X±S)	T	P
WEEK 2	71.32±1.81	69.880±1.90	2.737	0.009
WEEK 3	74.12±1.87	70.96±1.33	6.852	0.000
WEEK 4	82.4±2.12	73.68±3.60	10.42	0.000
WEEK 5	82.96±2.03	77.32±3.46	7.028	0.000
WEEK 6	83.32±2.01	80.56±1.75	5.161	0.000
WEEK 7	84.72±1.62	84.44±1.55	0.623	0.536
WEEK 8	85.2±1.35	84.72±1.56	1.106	0.261

Note: *P≤0.05, significant difference; P≤0.01, highly significant difference; P>0.05, no significant difference.*

As can be seen from Table 4, the independent samples T-test was conducted on the stage movement assessment data of the experimental group and the control group athletes respectively, and the results showed that the P-value in the data of the second week was 0.009, which was less than 0.01 with a highly significant difference, indicating that the movement learning of the experimental group athletes began to change in the beginning stage of the formation of movement skills. In the fourth week of the movement assessment the mean and standard deviation of the experimental group was 82.4±2.12, and the control group was 73.68±3.60, the mean value of the experimental group was much higher than that of the control group, and the score was improved by nearly 10 points, and the P-value of the two groups was 0.000, and P≤0.01 with highly significant difference, indicating that the experimental group of athletes had a more significant change in the stage of the pre-study period; in the sixth week of the movement assessment, the mean and standard deviation of the movement assessment of the athletes in the experimental group was 83.32±2.01, and that of the control group was 80.56±1.75, and the mean value of the experimental group was slightly higher than that of the control group, and the p-value was 0.000, p<0.05, and there was a significant difference between the two groups, which indicated that the mastery of the movement skills of the athletes in the experimental group was superior to that of the athletes in the control group; in the seventh week of the movement assessment, the mean and standard deviation of the movement assessment of the athletes in the experimental group was 84.72 and standard deviation of the experimental group was 84.72±1.62 and that of the control group was 84.44±1.55, with a p-value of 0.536, which was greater than 0.05, and there was no significant difference between the two groups. In the movement assessment of the eighth week, the P-value of the experimental group and the control group was 0.261, with no significant difference. By analyzing the results of each week's assessment, it can be seen that the experimental group and the control group of athletes in the classroom learning changes are greater, especially in the early and middle stages of the experiment, the changes are more significant, and only in the late stage is there no significant difference, the performance of the athletes in the movement assessment stage is analyzed as shown in the following figure.

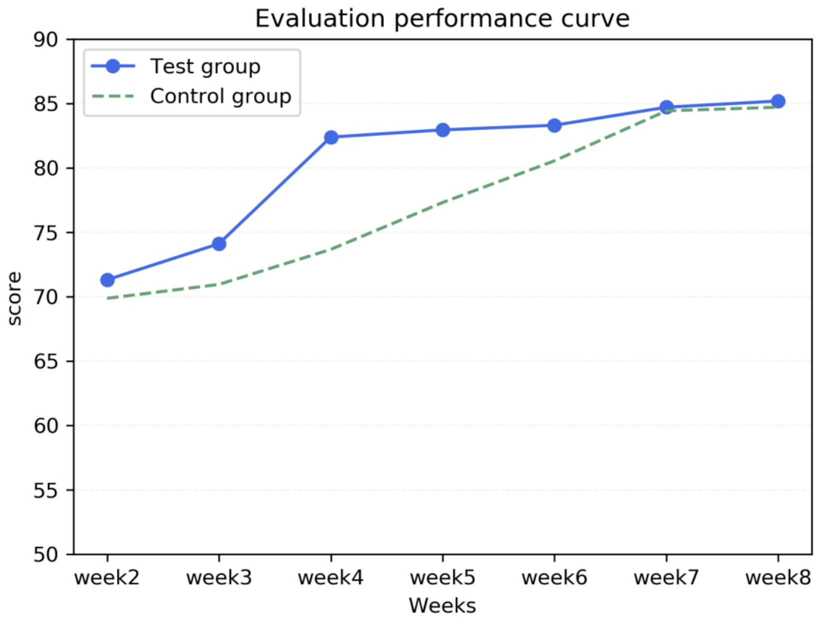

Figure 9: Comparative analysis of the assessment of each stage of movement between athletes in the experimental group and the control group

As can be seen in Figure 9 above, the application of Open Pose Skeletal Tracking Assisted Teaching System in the experimental group and the control group in the early stage of the experiment allows the athletes in the experimental group to understand the movements and learn the movements quickly, and the athletes' motivation to learn is higher due to the intervention of the intelligent teaching means, and the use of Open Pose Skeletal Tracking Assisted Teaching can correct and deepen the memory of the movements in time. Using Open Pose Skeletal Tracking to assist teaching can correct the movements in time and deepen the memorization of the movements, so that the athletes in the early stage of the program can get started quickly, and in the later stage, with the increase in the number of practice times of the athletes in the control group, they gradually catch up with the experimental group athletes, so the significant difference in the later stage of the program is not obvious, and even tends to be consistent.

In summary, utilizing the Open Pose Skeletal Tracking intelligent training environment facilitates the acquisition of motor skills, points to a high level of learning progress, and has an impact on the motivation of athletes during the free practice phase.

5. Discussion and analysis

5.1 The Effect of Open Pose Skeletal Tracking on Aerobics Performance in Aerobics Athletes

In Open Pose Skeletal Tracking based human pose recognition, the sequence of the human body first needs to be detected and segmented so that the various joint points of the human body can be accurately localized. Joints refer to points in various parts of the human body, such as the head, neck, shoulders, elbows, wrists, waist, knees, ankles, and so on. The positional information of these joint points plays a vital role in movement practice, training and performance in competitions. Based on the positional information of human joints, posture can be further recognized and analyzed. By identifying the positional relationship of each joint point of the human body, the movement posture, movement trajectory and other important information of the human body can be analyzed. For example, in the study of running posture, the Open Pose algorithm can be used to identify the movement status of each joint point in running, so as to more accurately analyze the quality of movement in the running process, and to find out the deficiencies of the athletes and improve them. From the application point of view, human posture recognition technology can be widely used in various sports training, competition evaluation and other aspects. For example, the use of human posture recognition technology for boxing evaluation can more accurately analyze the boxing movements of athletes, find out the shortcomings of boxing movements and improve them. At the same time, human posture recognition technology can also be widely used in the training of artistic sports such as dance and gymnastics, providing us with a finer perspective to understand the human movement process. In terms of aerobics stage movement formation, Open Pose Bone Tracking can intelligently design and adjust the stage movements according to the athletes' technical level and teaching objectives, so that the athletes can better master the key elements and technical difficulties of each movement.

After the experimental intervention, the athletes in the experimental group had an absolute advantage in all of the pre-test scores in the stage aerobics movement assessment. The reason for this is that Open Pose Bone Tracking can analyze and record athletes' movements in real time and provide them with accurate feedback and guidance, helping them to better understand and master aerobics movements and improve the accuracy and continuity of their movements. According to the theory of movement formation, it is believed that the formation of complete movements needs to go through four stages: generalization, differentiation, consolidation and automation. Athletes in the experimental group acquired movements faster than athletes in the control group, and the analysis of the movement skill formation stage is because the movement combinations learned in the early stage are still at the beginning level of basic movement skills (generalization and differentiation stage), so they will show extreme instability when facing the stage assessment, and the movements are easy to be deformed or incorrect, and the athletes in the experimental group utilized the Open Pose Skeleton Tracking Technique to assist the teaching of each of the two stages. The Open Pose Skeletal Tracking technique can provide accurate and effective guidance for each exercise, helping athletes to quickly form movement memories and improve the speed of movement formation. In addition, this technique can help athletes recognize and correct incorrect movements to avoid forming bad exercise habits and improve the effect of practice. And the experimental group in the stage of movement assessment also found that the experimental group and the control group's performance in the later stage of the basic convergence of no significant change is because the control group of athletes in the later stage of the practice after many times, according to the Pavlovian doctrine of higher neural activity based on the "generalization stage - differentiation stage - consolidation stage - automation of movement skills " divides the stages, which helps athletes' understanding and application. In these four stages, the control group's movements also gradually formed the automation stage of skills after repeated and extensive practice in the movement consolidation stage. Therefore, the two groups do not differ in the later stages of the movement assessment.

5.2 Impact of Open Pose Skeletal Tracking Technology on Predicting Sports Injuries

Injuries can have a huge impact on both the athlete and the team, and even become a key factor in determining the success or failure of a game. Dhanke et al. used a recurrent neural network (RNN) model to analyze an athlete's previous trajectory data and to predict the likelihood of sports injuries and the effectiveness of their treatment (Dhanke et al., 2022). However, limited data describing athletes' physical activity from the past creates an obstacle for injury prediction. Typically, the standard method for predicting injury risk is linear regression (Maffulli, Longo, Berton, Loppini, & Denaro, 2011), but it is only applicable to simple models and does not capture the complex nonlinear interactions between multiple elements. Nowadays, the Internet of Things (IoT) can rapidly change this situation thanks to the intervention of Electronic

Performance and Tracking Systems (EPTS). Georgios Kakavas et al. argued that the prediction of sports injuries is not a simple linear regression model, but rather combines both nonlinearity and complexity (Kakavas, Malliaropoulos, Pruna, & Maffulli, 2020).

Artificial intelligence neural networks are able to capture complex patterns in a hierarchical manner, recognizing nonlinear functions of observed variables through a data-driven learning process, which is not possible through linear models. In the medical field, it has become a reality to input many factors into a computer system to assess human health and give virtual exercise prescriptions, and the human body, as a complex system, also requires a broader approach to the prediction of sports injuries - the complex systems approach. In recent years, the complex systems approach has been widely applied to complex problems in medicine, biology, economics and social sciences. In the prediction of sports injuries, the use of artificial intelligence models to compute nonlinear relationships between observable variables to deal with complex phenomena such as soft tissue injuries are undoubtedly a great advantage in assessing the risk and at the same time helping to predict the occurrence of sports injuries.

5.3 Impact of Open Pose Bone Tracking Technology for Injury Recovery

With the increasing demand for intelligent monitoring systems for sports, people are gradually beginning to pay attention to the integration of artificial intelligence with the field of sports rehabilitation. Relevant AI devices can not only help athletes monitor their physical responses during high-intensity training, but also cope with the process of repairing sports injuries after exercise in order to shorten the recovery time. A rehabilitation training method based on artificial intelligence and virtual reality technology, and conducted group experiments on injured members of a track and field team. The results showed that the rehabilitation training based on artificial intelligence and virtual reality technology can provide a more personalized rehabilitation training method through the analysis of the athlete's body functions, and the efficiency and quality of rehabilitation can be improved compared with the traditional recovery training. While Nwachukwu et al developed an algorithm based on LASSO regression technique for modeling patients with femoral acetabular impingement, the AI model provided data showing mood disorders, symptom duration, and other data to help improve clinical decision making and postoperative patient care.

6. Conclusion

With the wave of intelligence sweeping in, artificial intelligence technology represented by big data, Internet of Things, etc. is deeply integrating with all walks of life and empowering their development. As an important and indispensable part of China's competitive sports, sports training should seize the technological change of the era of artificial intelligence to bring new development opportunities and innovative changes. Artificial intelligence has unparalleled advantages of data analysis and real-time monitoring in the selection, training, participation, competition, and adjustment of training programs, etc. We need to pay attention to the relevant ethical and privacy issues while making full use of this "training tool" to avoid the drawbacks arising from its use. In the future, with the gradual improvement of AI-related laws and regulations and the establishment of industry standards, more and more sports will adopt the new concept of intelligent training, realizing the "wisdom" empowerment, promoting the comprehensive strength of China's athletic sports and laying a solid foundation for the comprehensive realization of the ambitious goal of a strong sports nation!

Through experimental verification, it is proved that: Open Pose Skeletal Tracking Assisted Teaching System has strong relevance, can provide real-time action feedback and action correction suggestions for athletes' action practice, and has a promotion effect on athletes' mastery of complete sets of actions; and it is found that in the stage assessment of actions, it is appropriate to use in the beginning stage of the formation of the action, i.e., the generalization and differentiation stage, which has a greater help to the formation of the athletes' memory of actions and can stimulate the athletes' learning enthusiasm and motivation. This is helpful to the formation of athletes' movement memory, and can stimulate athletes' learning enthusiasm and motivation. However, the effect on the overall performance of teaching and performance is not obvious.

Acknowledgements:

1.The 2022 regular project of Shaanxi Provincial Sports Bureau (Project Name：Study on the Intangible Cultural Heritage of Sports in Shaanxi Province -- Taking Ansai Waist Drum as an example. Project No.: 2022422).

2.Shaanxi province Philosophy Social Science Research Special General Project (Project Name: Sports and Tourism Integration Development Research, Project No.: 2023HZ1628).

3.Basic Research Program of natural sciences of Shaanxi province (Project Name: Study on the mechanism of physical exercise in alleviating anxiety-like depression by regulating Wnt/β-catenin signaling pathway, Project No.: S2023-JC-YB-0324).

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