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Retraction

Retracted: Attitude Monitoring Algorithm for Volleyball Sports Training Based on Machine Learning in the Context of Artificial Intelligence

Security and Communication Networks

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Security and Communication Networks has retracted the article titled "Attitude Monitoring Algorithm for Volleyball Sports Training Based on Machine Learning in the Context of Artificial Intelligence" [1] due to concerns that the peer review process has been compromised.

Following an investigation conducted by the Hindawi Research Integrity team [2], significant concerns were identified with the peer reviewers assigned to this article; the investigation has concluded that the peer review process was compromised. We therefore can no longer trust the peer review process, and the article is being retracted with the agreement of the Chief Editor.

References

[1] Z. Sun and P. Sun, "Attitude Monitoring Algorithm for Volleyball Sports Training Based on Machine Learning in the Context of Artificial Intelligence," *Security and Communication Networks*, vol. 2022, Article ID 2907393, 10 pages, 2022.

[2] L. Ferguson, "Advancing Research Integrity Collaboratively and with Vigour," 2022, https://www.hindawi.com/post/advancing-research-integrity-collaboratively-and-vigour/.

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Research Article

Attitude Monitoring Algorithm for Volleyball Sports Training Based on Machine Learning in the Context of Artificial Intelligence

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With the development of artificial intelligence technology and information technology, the posture of volleyball training is becoming increasingly strict. By analyzing the dynamic training posture monitoring algorithm, the posture information of the human body can be directly obtained, which enables more efficient management of volleyball sports training. This paper aims to study how to monitor volleyball training posture and give suggestions based on machine learning in the context of artificial intelligence. The traditional method of manually detecting volleyball training postures is too subjective and cannot be used to judge the movements. Therefore, this paper proposes an algorithm for human posture monitoring and studies human posture recognition. Human gesture recognition has been widely used in many fields. The experimental results in this paper show that the corrected serve deviation rate of five volleyball players is 13.1% at the highest and 11.3% at the lowest after the traditional manual visual monitoring. The highest error is 0.70 m and the lowest is 0.63 m. The overall error is high. The corrected service deviation rate of the machine learning-based attitude monitoring algorithm is 3.5% at the highest and 2.7% at the lowest. The highest error is 0.24 m and the lowest is 0.19 m. The overall error is much lower than the former. This also shows that the posture monitoring algorithm based on machine learning can effectively detect the movement of volleyball players. This enables athletes to correct their mistakes in a timely manner, improve training efficiency, and improve their own strength.

1. Introduction

Machine learning is the study of how to use computers to simulate or implement human learning activities. It is one of the most intelligent features and one of the most cutting-edge research fields in artificial intelligence. Since the 1980s, machine learning has attracted extensive interest in the artificial intelligence community as a way to achieve artificial intelligence. Sports and science and technology are inseparable. Modern science penetrates into all aspects of sports and plays an increasingly important role. To comprehensively improve the training level and performance of volleyball players and promote the development of sports, a volleyball training posture monitoring algorithm based on machine learning is proposed. The detection and action understanding of video objects is a hot issue in the field of machine vision. For example, it is widely used in human-computer interaction systems, action monitoring, sports training, posture monitoring, etc. By monitoring the training posture, it can determine whether the training posture of the athlete is correct, to help the coach to train the athlete more professionally.

For a long time, the state has placed a high priority on improving students' overall quality to encourage the holistic development of morals, intelligence, and physical state. However, due to the influence of exam-oriented education, physical education teachers are in low supply in rural schools. As a result, physical education in primary schools is of poor quality. Because of the enormous number of students, physical education teachers or coaches in primary and secondary schools are frequently unable to guide students in training. People are combining virtual reality with other technologies as computer technology advances. With the progress of computer technology, people are combining virtual reality with other technologies, realizing scientific supplementary training of sports and eliminating the impartial training state based on experience.

The innovations of this paper are as follows: (1) It introduces the relevant theoretical knowledge of artificial intelligence technology and machine learning and proposes a human posture monitoring algorithm based on machine learning. It analyzes how attitude monitoring algorithms work in volleyball sports training. (2) It conducts an experimental comparison between the human body posture monitoring algorithm and the traditional monitoring algorithm. Through the analysis, it can be known that the human body posture monitoring algorithm is beneficial to identify and monitor the wrong movements of volleyball players in training and correct them in time.

2. Related Work

With the advent of the information age, the development of volleyball has also injected the concept of science and technology. Castro H validated visual behavior by analyzing the quality of extreme attack (EA), central attack (CA), and environment (SE) in volleyball players and other sports athletes. He used the tracking system to evaluate the volleyball scene. He also used independent tests to compare groups in the following cases: EA, SE, and CA. The scholar wanted to analyze how volleyball players differed from other players in certain sports behaviors. However, he did not have a clear process, and the logic was not high [1]. Havinga et al. discovered that wireless sensor networks (WSNs) usually consist of a large number of small, low-power, and inexpensive sensor nodes distributed over a large area. WSN can be thought of as a large distributed database. Users can make some queries on it, or they can react and push information or alerts when an event is detected. Designing effective and efficient event detection techniques to cope with limited WSN resources is the goal of his research. The scholars wanted to use WSN to detect unsafe behavior, but they had no specific experimental subjects to prove whether the method was effective [2]. Yang et al. found that efficient reservoir operation requires decision makers and operators to understand how reservoir inflows changes under changing hydrological and climatic conditions. Artificial intelligence and data mining techniques have been increasingly used to aid reservoir flow forecasts over the last decade. Random Forests (RF), Artificial Neural Networks (ANN), and Support Vector Regression (SVR) were among the techniques they employed. The results show that the three methods can provide satisfactory monthly reservoir inflow statistics. The scholars proposed to use three methods to predict the water volume of the reservoir and believed that good results were obtained. However, they did not explain how to use these three methods to predict the reservoir water volume [3]. Hutson found that the booming field of artificial intelligence (AI) was grappling with a replication crisis. Unpublished code and sensitivity to training conditions make it difficult for AI researchers to discover many key results. Replicability of AI was on the agenda at the Association for the Advancement of Artificial Intelligence meeting. Some teams diagnose the problem. One of the teams came up with ways to mitigate the problem. The scholar briefly described the crisis of replication that AI faces. However, he did not explain how to solve this crisis [4]. Lemley et al. found that the past few years have witnessed an increase in research activity for advanced training of convolutional neural networks (CNNs) in machine learning. It led to the emergence of new graphics processing unit (GPU) based hardware. This hardware enables these large datasets to be processed in a reasonable time frame. Various long-standing problems in machine learning, artificial intelligence, and computer vision have improved dramatically. The scholars believe that the emergence of convolutional neural networks has solved long-standing problems in artificial intelligence. As for how to solve these problems, the scholars did not explain [5]. Price and Flach found that state-of-the-art tools from machine learning and artificial intelligence were gradually being automated; however, there was still much room for improvement. They found that key tasks could be accomplished using feature extraction commonly used in machine learning. These streamlining tools also provide suggestions for improving the peer review process. To make the meeting more smoothly, they suggested that people should use machine learning in it. The scholars found that machine learning can automate meetings. However, they did not explain how to automate meetings [6].

3. Human Posture Monitoring Algorithm Based on Machine Learning

3.1. The Necessity of Machine Learning-Based Human Posture Monitoring in Volleyball. Artificial intelligence is a branch of computer science. It attempts to understand the essence of intelligence and produce a new intelligent machine that can respond in a similar way to human intelligence. Research in this area includes robotics, language recognition, image recognition, natural language processing, and expert systems. Now, artificial intelligence (AI) is integrated into every corner of people's lives. The processing categories of artificial intelligence are very broad, including visual images, sound signals, textual data, and high-dimensional information extracted from them. Among them, the processing of visual images is the eye of artificial intelligence and is an essential topic. The focus of computer vision is in the field of object detection and recognition [7].

The Volleyball World Cup is the youngest of the three official competitions. It has gradually become an Olympic trial since the year of competition was changed in 1991. Volleyball is a traditional competitive sport in China that has won many medals in major events, but it still requires scientific analysis of athletes' movements. If improper posture in volleyball training is not rectified for a long time, it will become a bad habit, which is difficult to break in the future [8]. Furthermore, due to the high expense of one-on-one volleyball instruction, it is difficult to effectively modify personal training habits, the positive effect of training is not visible, and the efficiency is low [9]. The classic training posture of volleyball is shown in Figure 1.

As shown in Figure 1, throughout the volleyball process, there are some important postures that affect an athlete's

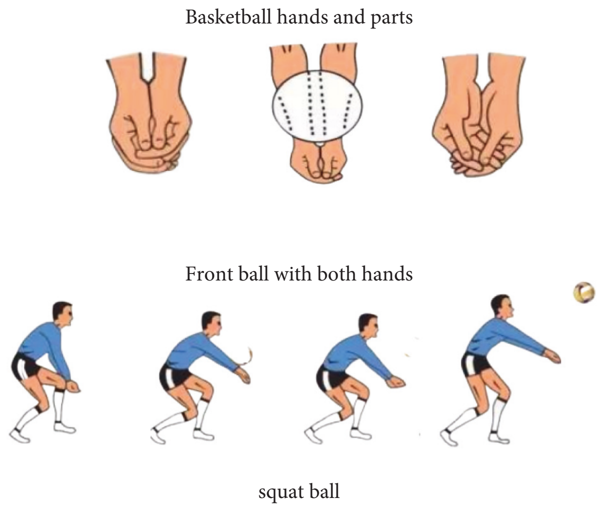

FIGURE 1: Classical volleyball training poses.

performance. These important postures are essential for success. In the training process, whether the posture of volleyball in the past is correct is mainly based on the experience of the coach. This is not only a waste of human resources, but also susceptible to subjective factors. Therefore, scientifically and rationally analyzing volleyball can help athletes to regulate their movements [10].

In recent years, with the rapid development of computer information technology, the research on motion monitoring of human body posture has attracted attention, and people's demand for it has become higher and higher. Since entering the twenty-first century, people are increasingly concerned about the development of sports. Object detection and gesture recognition techniques are increasingly applicable [11].

3.2. Human Motion Pose Detection Algorithm Based on Machine Learning. Machine learning is a multidomain interdisciplinary subject. It involves many disciplines such as probability theory, statistics, approximation theory, convex analysis, and algorithm complexity theory. It specializes in how computers simulate or realize human learning behaviors to acquire new knowledge or skills. It reorganizes the existing knowledge structure to continuously improve its performance. Deep learning is essential in machine learning, and it has also been widely used in speech recognition, computer vision, and other fields [12].

Therefore, this paper uses posture monitoring to judge whether the movement posture in volleyball training is standard. It needs to select several feature points to track the volleyball object. As a professional motion analysis algorithm, attitude monitoring algorithm is mainly used in the field of motion analysis. It can provide professional sports analysis for volleyball players to improve sports performance. It digitally processes the movement trajectory of the volleyball object and provides data support for monitoring the volleyball posture [13].

The human body is made up of 206 bones. To reduce the complexity of human skeleton modeling, the human skeleton can be simplified into a tree structure with rigid body characteristics. The motion posture of each limb in the human skeleton model is determined by the three-dimensional rotation angle and spatial position of the joints linking the two bones. Choosing an appropriate expression method and form of human motion parameters can accurately and efficiently return and quantify the motion state of human bone. Establishing an optimal human posture monitoring algorithm can not only improve the overall performance of the system, but also meet the transmission, storage, and computing requirements more efficiently [14].

3.2.1. Basic Method of Attitude Description. Euler's theorem is a property about congruence. Euler's theorem on complex numbers is also known as Euler's formula. It is considered one of the most wonderful theorems in the mathematical world. The angle of the three rotations is the Euler angle [15]. The detailed process of the three rotations is shown in

$$OX_0Y_0Z_0 \xrightarrow{A_0,K_X} OX_1Y_1Z_1 \xrightarrow{Y_0,K_Y} OX_2Y_2Z_2. \tag{1}$$

It assumes that coordinate system $OX_0Y_0Z_0$ gets coordinate system $OXYZ$ after rotation transformation. The rotation angle ϕ around the X axis is as

$$A_x(\phi) = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos\phi & \sin\phi \\ 0 & -\sin\phi & \cos\phi \end{pmatrix}. \tag{2}$$

The rotation angle θ around the Y axis is shown in

$$A_y(\theta) = \begin{pmatrix} \cos\theta & 0 & -\sin\theta \\ 0 & 1 & \sin\theta \\ \sin\theta & 0 & \cos\theta \end{pmatrix}. \tag{3}$$

The rotation angle ψ around the Z axis is shown in

$$A_z(\psi) = \begin{pmatrix} \cos\psi & \sin\psi & 0 \\ -\sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{pmatrix}. \tag{4}$$

The attitude matrix is also called the direction cosine matrix. It is a matrix formed by the direction cosines between the basis vectors of two different sets of standard orthonormal bases. The determinant of the attitude matrix also includes the rotation order. When representing Euler angles on a navigation sequence, it often adopts the rotation order of *zyx*. Euler angle is the rotation angle of an object around the three coordinate axes (x, y, z) of the coordinate system. Here, the coordinate system can be the world coordinate system or the object coordinate system. The rotation order is also arbitrary. The *Zyx* Euler angle rotation process is shown in Figure 2.

As shown in Figure 2, the vector rotates around the z-axis, y-axis, and x-axis in turn. The angles of the three rotations are ψ, θ, and ϕ in order. The resulting vector after rotation is $v' = [x', y', z']$. The calculation formula of its coordinate transformation can be obtained from

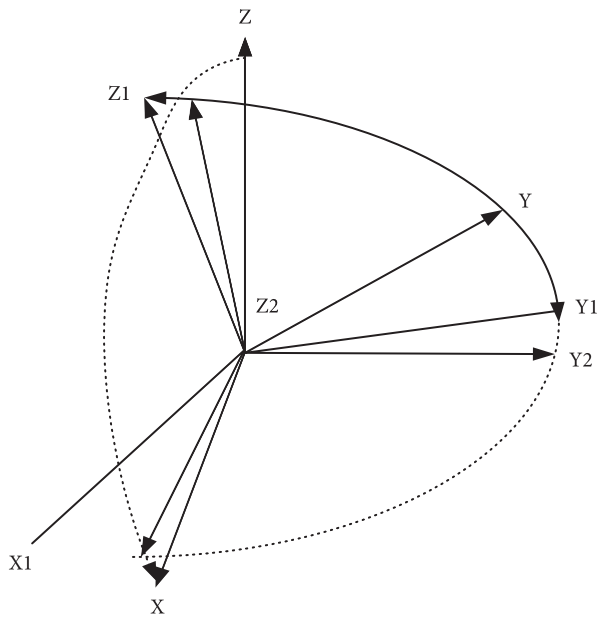

Figure 2: Schematic diagram of the rotating Euler angle.

$$v' = A_x(\phi)A_y(\theta)A_z(\psi)v. \tag{5}$$

When the three rotation order is described by matrix multiplication, the corresponding standard rotation matrix should be multiplied in turn according to the reverse order of the rotation order. If the rotation is in the order of the *zyx* axis, then its rotation matrix should be written as

$$R = A_x(\phi)A_y(\theta)A_z(\psi). \tag{6}$$

It uses Euler angles to indicate that the rotation has a gimbal deadlock problem. That is, after the rigid body rotates 90° around an axis, the two axes of rotation coincide with the two axes before the rotation, but the axes are opposite. This state can also be obtained by another rotation. Therefore, if the former rotation method is adopted, one rotational degree of freedom will be lost. This phenomenon is the universal lock phenomenon [16].

3.2.2. Image Filtering. Image filtering is to suppress the noise of the target image while preserving the details of the image as much as possible. It is an indispensable operation in image preprocessing. The quality of its processing effect will directly affect the effectiveness and reliability of subsequent image processing and analysis. From the processing domain point of view, it is generally divided into two categories: spatial-domain filtering and frequency-domain filtering [17].

It finally replaces the gray value of the pixel in the original image with the arithmetic mean of all pixel gray levels in the template neighborhood S, thereby realizing image filtering. Mean filtering is a typical linear filtering algorithm. It refers to giving a template to the target pixel in the image, and the template includes the adjacent pixels around it. It then replaces the original pixel value with the average of all pixels in the template. Its formula is as follows:

$$g(a,b) = \frac{1}{N \times N} \sum_{(i,j)\in s} f(i,j). \tag{7}$$

Its neighborhood template S is a square window (a,b) centered on point $N \times N$.

Median filtering is a nonlinear signal processing technique based on ranking statistics theory that can effectively suppress noise. The process of median filtering is shown in Figure 3.

As shown in Figure 3, it considers both the pixel spatial difference and the intensity difference. It replaces the gray value of the pixel with the weighted average of all pixel gray levels in the template neighborhood. Image filtering has two purposes: one is to remove noise, and the other is to protect image feature information for image analysis. There are two requirements for filtering processing. One is to make the image clear and improve the visual effect. Another is to try to keep important feature information such as image edges and contours [18]. The bilateral filtering meets the requirements of filtering processing and achieves the purpose of filtering processing, which is beneficial to the subsequent target detection and recognition.

The standard error is defined as the square root of the mean of the sum of the squares of the errors of each measurement, so it is also called the mean square error. Therefore normalization refers to controlling the mean squared error within a certain range. It generally uses the normalized mean square error (NMSE) and the peak signal-to-noise ratio PSNR to evaluate the image processing effect.

$$\text{NMSE} = \frac{\sum_{i=0}^{N}\sum_{j=0}^{M}(g(i,j) - f(i,j))^2}{\sum_{i=0}^{N}\sum_{j=0}^{M}(i,j)^2}. \tag{8}$$

The larger the value of NMSE, the stronger the algorithm performance. When the 3×3 window template is also used for processing, the filtering parameters of different filtering methods are shown in Table 1.

As demonstrated in Table 1, the mean filtering algorithm is the simplest and easiest to implement, and it requires the least amount of time. The strongest denoising capacity comes from filtering, which is less impacted by noise. The strongest detail protection is provided by bilateral filtering. This study chooses the bilateral filtering algorithm based on the needs of this article for the system's real-time performance and the algorithm's requirements for the integrity of the picture edge information [19].

3.3. Feature Extraction of Volleyball Posture. The research of human gesture recognition is very difficult. Due to the nonrigid characteristics of the human body and the diversity of poses, it is difficult to use a qualitative framework to uniformly describe the classification of poses [20]. At present, there are a variety of human pose models for different application scenarios and different purposes. The descriptions of their human posture features are also different. Considering the complexity of volleyball human posture and the complexity of the algorithm, this paper proposes a human posture recognition algorithm based on multifeature fusion and image similarity. It improves on the feature description

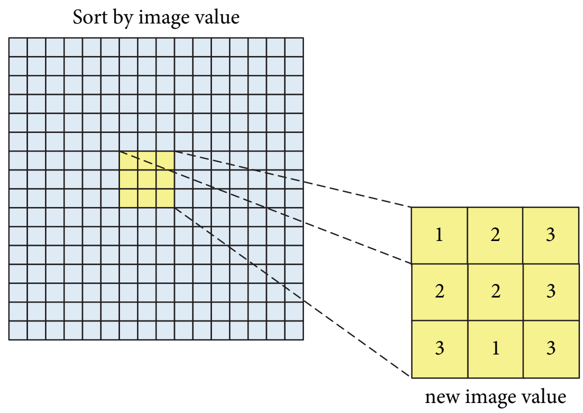

Figure 3: Median filtering process.

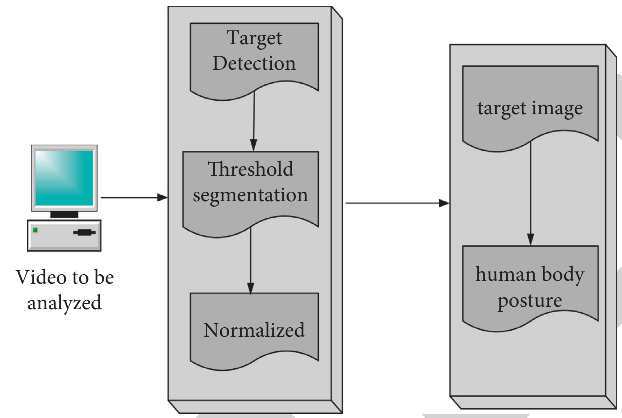

Figure 4: Structure diagram of human pose modeling.

Table 1: Filter parameters for different filtering methods.

Filter method	Time/ms	NMSE/10^{-3}	PMSR
Mean filter	1.18280	3.6231	28.8000
Gaussian filter	2.71176	3.21808	30.445
Median filter	18.0607	4.25841	29.1177
Bilateral filtering	5.04451	0.0162014	53.1410

method based on low-level image information. It can detect hands and human bodies in images or video in real time. It supports multiple functions such as key point detection, gesture recognition, and human contour segmentation. It is used in gesture control, somatosensory games, portrait matting, video background replacement, and other scenarios. Its structural block diagram is shown in Figure 4.

As shown in Figure 4, according to the complexity of the volleyball movement posture features, it can be divided into three-dimensional and two-dimensional features. The 3D features are three-dimensional enough to mimic the shape of the human body as much as possible, which can avoid problems such as occlusion and deformation in the video. However, high computational complexity, large space complexity, and many training parameters affect the real-time performance of the system. Although the two-dimensional pose feature is not as accurate as the former, its realization process is simple and easy. It can adequately characterize basic poses. Therefore, in monocular detection, two-dimensional pose features are often used in human pose recognition.

In the business intelligence solution of multidimensional analysis, common models can be divided into star model and snowflake model according to the relationship between fact table and dimension table. When designing a model for logical data, it should be considered whether the data is organized in a star schema or a snowflake schema. The eight-star model is improved from the traditional star model. It refers to the feature description model formed according to the eight local contour poles and centroid points of the human target. The human body pose model is established as:

$$\text{feature} = \{D, A, e\}. \tag{9}$$

Among them, e is the eccentricity of the human target. The specific feature extraction process is as follows:

It calculates the centroid (a_c, b_c) of the human target in

$$a_c = \frac{1}{N_b}\sum_{i=1}^{N_b} a_i, \qquad b_c = \frac{1}{N_b}\sum_{i=1}^{N_b} b_i, \tag{10}$$

where N_b is the number of target pixels. It divides the target into four parts by horizontal and vertical lines passing through the centroid. Based on the overall outer contour of the target, it extracts eight local contour pole coordinates of the rightmost, uppermost, leftmost, and lowermost contours in each part.

It calculates the Euclidean distance between 8 local contour poles $(a_i - a_c)^2$ and centroid $(b_i - b_c)^2$, denoting d_i, respectively. Its calculation formula is as

$$d_i = \sqrt{(a_i - a_c)^2 + (b_i - b_c)^2}, \quad i = 1, 2, \ldots, 8. \tag{11}$$

The extraction process is shown in Figure 5.

As shown in Figure 5, it calculates the minimum angle formed by the eight straight lines and the horizontal line through the straight lines between the eight local contour poles and the centroid point, which is expressed as a_i. Its calculation formula is as

$$a_i = \arccos\left(\left|\frac{a_i - a_c}{d_i}\right|\right) \times \frac{180}{\pi}. \tag{12}$$

The unified definition of eccentricity is the ratio of the distance from the moving point to the focal point and the distance from the moving point to the directrix. It cuts the largest circumscribed rectangle of the human body contour and obtains the largest inscribed circle along the rectangle. Then the eccentricity describes how far the circle deviates from the ideal circle. Its calculation formula is as

$$e = \sqrt{1 - \frac{a^2}{b^2}}. \tag{13}$$

Here, a is the smaller of the human target height H and width W, and b is the larger of the height H and width W. H is the unified image height after target normalization, and W is the width after scaling according to the original target

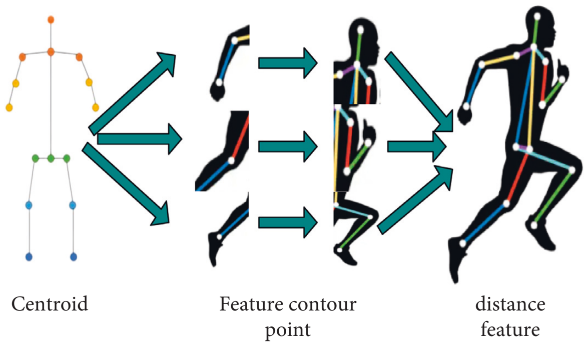

Figure 5: The feature extraction process of the local contour pole distance of the eight-star model of the human body.

ratio. The specific values of the eccentricity comparison of different postures are shown in Table 2.

As shown in Table 2, from the analysis of the experimental data, it can be seen that different postures have their own eccentricity range. For most standing postures, the eccentricity is large, which is similar to a flat ellipse. On the contrary, for the posture of body bending or overstretching, the eccentricity is small and approximates to an ideal circle.

3.4. Volleyball Gait Characteristics and Support Point Detection. There are two states of the legs when walking in volleyball. One is the support period when the foot is on the ground, and the other is the leg swing period when the foot is off the ground. The definition of support period and leg swing period is as follows. When the heel of a leg hits the ground until the toe is off the ground, it is called the support period of the leg. When the toe of a leg is off the ground and the heel hits the ground after stepping, it is called the swing period of the leg.

The Euclidean norm refers to the distance norm in the usual sense. For example, in Euclidean space, it represents the distance between two points. In this paper, the Euclidean norm of the three-axis data of the accelerometer fixed on the foot is used to judge whether the leg is in the support period or the swing period. According to the definition of Euclidean norm, the three-axis acceleration values output by the multisensors bound to the left and right feet can be calculated separately. The calculation formula is as

$$\begin{cases} \mathrm{Acc}_{\mathrm{left}} = \sqrt{a_{x,\mathrm{left}}^2 + a_{y,\mathrm{left}}^2 + a_{z,\mathrm{left}}^2}, \\ \mathrm{Acc}_{\mathrm{right}} = \sqrt{a_{x,\mathrm{right}}^2 + a_{y,\mathrm{right}}^2 + a_{z,\mathrm{right}}^2}. \end{cases} \tag{14}$$

The accelerometer data of the left and right feet were collected while walking, and the Euclidean norm was calculated, respectively. The straight line and the dotted line represent the data of the left and right feet, respectively. The Euclidean norm is actually the extension of the three-dimensional space distance to the Euclidean space. The result is shown in Figure 6.

As shown in Figure 6, because the original data fluctuates greatly, it is not conducive to the analysis of the data, so the

Table 2: Eccentricity comparison of different volleyball postures.

Serial number	Attitude	Eccentricity e
a	Stand	0.833523
b	Walk	0.810440
c	Run	0.745703
d	Jump	0.834522
e	Walk sideways	0.743703
f	Spread out	0.540802
g	Bend over	0.526440

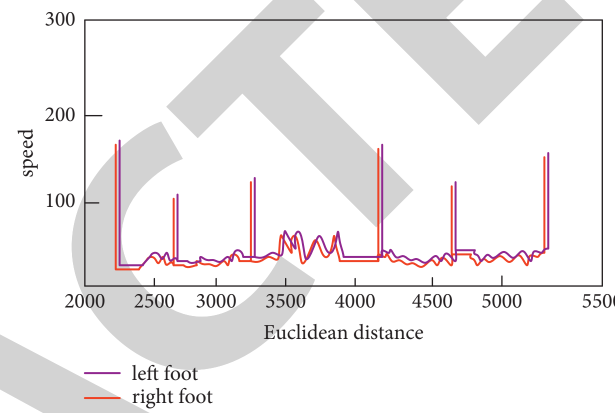

Figure 6: Euclidean norm of left and right foot acceleration raw data.

data is filtered by the window function. The result after filtering and denoising is shown in Figure 7.

As shown in Figure 7, when walking, the foot in the support period is stationary relative to the ground, so the Euclidean norm of its acceleration component is approximately equal to the modulus value of the local gravitational acceleration. The Euclidean norm of the acceleration component increases rapidly when the foot lifts off the ground in the stance phase and the leg becomes in the swing phase. At the same time, the other leg transitions from the swing phase to the support phase, and the Euclidean norm value of the acceleration component decreases rapidly until around the value of the acceleration of gravity.

3.5. Quaternion Attitude Fusion Algorithm Based on Motion Attitude Monitoring

3.5.1. Complementary Filter. The dynamic and static performance of the three sensors, speedometer, gyroscope, and magnetometer, are different. The dynamic performance of the gyroscope is good, but it is easily interfered by high-frequency noise. Based on this, the data of the three sensing devices can compensate each other in the frequency domain. Therefore, the complementary filter can effectively fuse the data of the three devices and reduce the interference of high-frequency noise on the accelerometer and magnetometer. It also compensates the accumulated error caused by gyro drift and improves the accuracy of attitude calculation.

According to the definition of the complementary filter, the attitude matrix of the multisensing unit can be written as

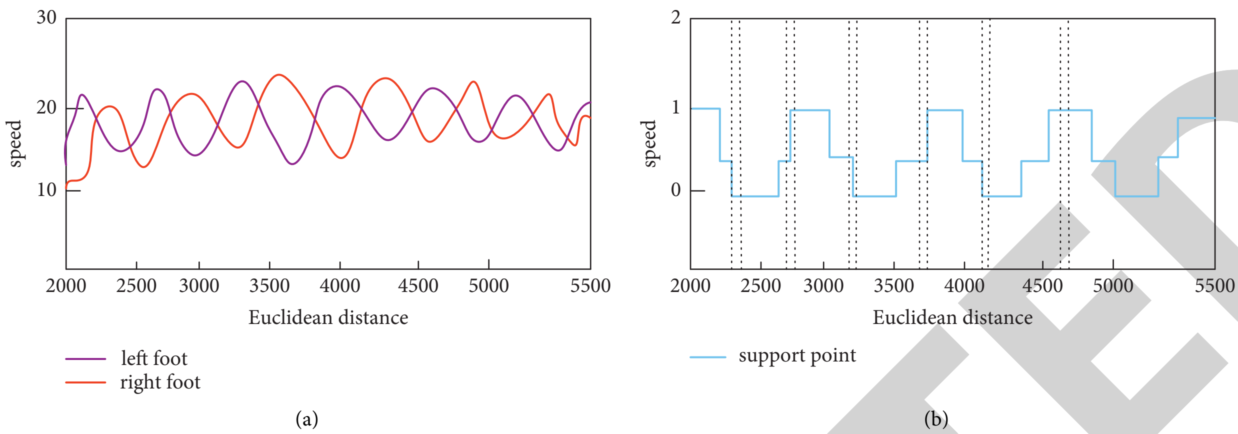

FIGURE 7: Euclidean norm of left and right foot acceleration data and support leg detection. (a) Euclidean norm of left and right foot acceleration data. (b) Support point detection.

$$R(s) = R_{am}(s)G_L(s) + R_\omega(s)G_H(s). \tag{15}$$

Here, $G_L(s)$ and $G_H(s)$ are the transfer functions of complementary filters. The two can well fuse the data of each sensor and effectively eliminate high-frequency noise. The transfer function is

$$G_L(s) = \frac{C(s)}{s + C(s)}, \tag{16}$$

where $C(s)$ is the ideal PID controller transfer function.

3.5.2. Hybrid Filter. According to the characteristics of complementary filter, this paper designs an adaptive hybrid filter fusion algorithm based on Gauss-Newton algorithm and complementary filter. It uses the convergence direction of the Gauss-Newton method as the observation quantity to correct the accumulated error of the gyroscope. It imports the gravity vector and geomagnetic reference vector, adjusts the parameters of the complementary filter adaptively, and performs pose calculation.

It uses the pose calculated by the optimized Gauss-Newton algorithm. It is used as the observation vector to improve the dynamic performance of the motion pose. The differential formula of the attitude rotation quaternion is shown in

$$\omega^b = [0, \omega_x, \omega_y, \omega_z]. \tag{17}$$

According to the problem of nonlinear minimum mean square error, the objective function is constructed as

$$f(q_{am,t}) = \frac{1}{2}\varepsilon(q_{am,t})^T, \tag{18}$$

where $q_{am,t}$ is the rotation quaternion solved by the Gauss-Newton algorithm and $(q_{am,t})^T$ is the error function.

The similarity measure is to compare the degree of proximity between each sample, generally by calculating the "distance" between the samples. The commonly used method is Euclidean distance such as

$$d(a,b) = \left(\sum_{i=1}^{n} (a_i - b_i)^2\right)^{1/2}. \tag{19}$$

The gain weight of the complementary filter is a fixed value. The adaptive complementary filter proposed in this paper optimizes the pose calculation results by combining the advantages of the complementary filter and the Kalman filter and adjusting the weights of the different algorithms in real time. Low-pass filtering is included in the optimized calculation formula. Therefore, the change rate of the adaptive complementary filtering parameters can be reduced, and the continuity and stability of the system can be improved.

4. Experimental Analysis of Human Pose Detection Algorithm Compared with Other Algorithms

4.1. Accuracy Analysis of Human Pose Detection Algorithm. Kalman filtering algorithm and complementary filtering algorithm are the mainstream attitude monitoring filtering algorithms. The gradient descent method combined with the hybrid filtering algorithm of complementary filtering has very low adaptability. To verify the reliability and effectiveness of the algorithm in this paper, it is compared with the complementary filtering algorithm (CF), the extended Kalman filtering algorithm (EKF), and the gradient descent algorithm (GDA).

Linear acceleration due to free motion affects the accuracy of posture monitoring. In this paper, the horizontal sliding experiment is used to verify the filtering effect of the algorithm with linear acceleration. It places the pose measurement unit on the surface of the water platform, performs horizontal back-and-forth sliding, and fuses the data with 4 algorithms, as shown in Figure 8.

As shown in Figure 8, through the comparative analysis of the four algorithms, it can be known that the algorithm proposed in this paper can accurately monitor a series of movements of volleyball players in sports. It can accurately

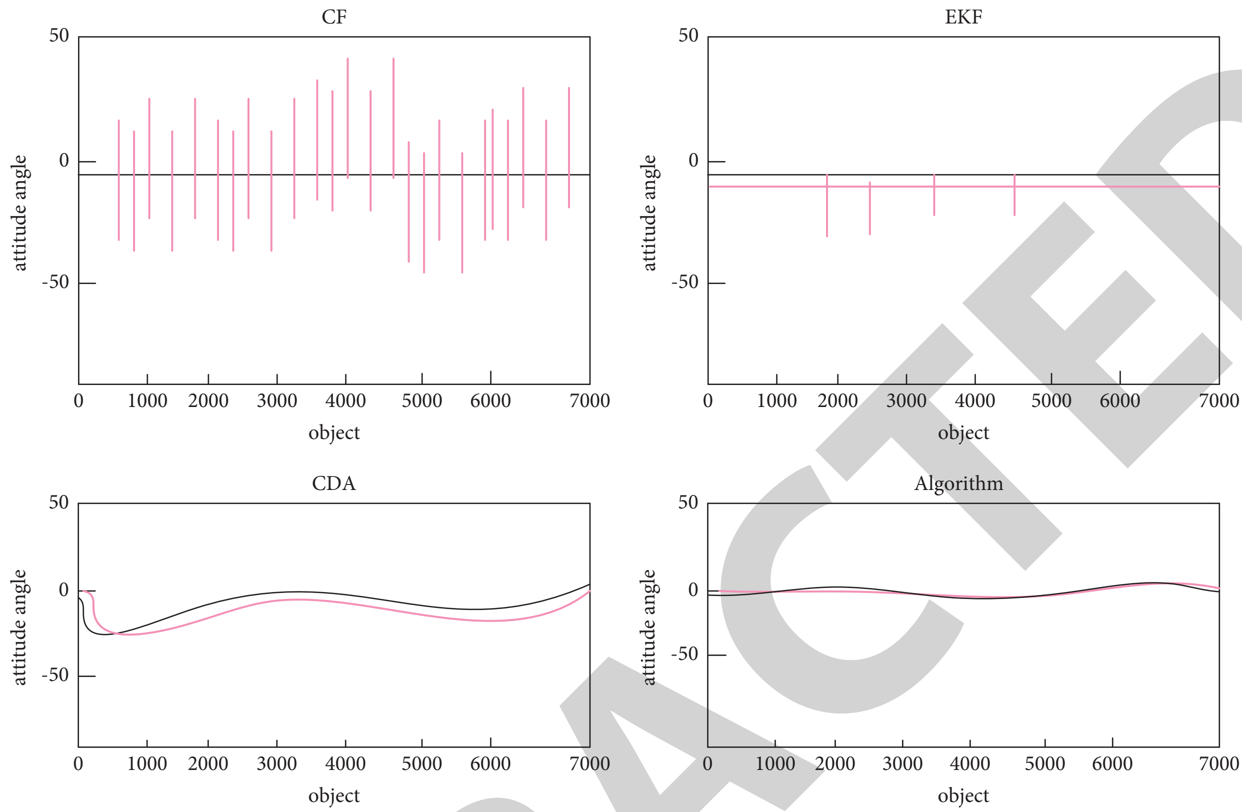

Figure 8: The accuracy of four algorithms after fusion of data.

Table 3: Corrected serve deviation rate for traditional manual eye monitoring.

Serial number	Error end point offset rate (%)	Error (m)
Serve 1	12.6	0.69
Serve 2	13.1	0.70
Serve 3	11.3	0.63
Serve 4	11.9	0.65
Serve 5	12.2	0.67

Table 4: Corrected serve offset rates for machine learning-based attitude monitoring algorithms.

Serial number	Error end point offset rate (%)	Error (m)
Serve 1	3.5	0.24
Serve 2	2.7	0.19
Serve 3	3.2	0.23
Serve 4	3.0	0.22
Serve 5	3.1	0.21

measure the joint rotation angle when the human body moves.

To ensure the universality of the algorithm, five volleyball players were required to test the server after the traditional manual visual monitoring and the machine learning-based attitude monitoring algorithm were corrected. The statistics of the test results are shown in Tables 3 and 4.

As shown in Tables 3 and 4, the corrected service deviation rates of the machine learning-based attitude monitoring algorithms in the three-dimensional space are all less than 4%. This shows that the posture monitoring algorithm based on machine learning is beneficial to the correction of volleyball wrong movements.

4.2. Auxiliary Training Experiment Based on Pose Similarity. As the system's input, it chooses 50 frames of serving photographs of volleyball trainers and coaches. It generates a comparison of joint angles and the similarity of each frame's trajectory. A demonstration of auxiliary training using joint angle trajectories is shown below. The solid line depicts the change in the coach's joint angle, while the dotted line depicts the change in the trainer's joint angle, as shown in Figure 9.

As shown in Figure 9, pose similarity is to evaluate the similarity of the actions of the coach and the trainer in each frame of image. Pose similarity is measured by Euclidean distance. The smaller the Euclidean distance value is, the closer it is to 0, indicating that the two actions are more similar. From the analysis of the pose similarity curve of each frame image, it can be known that the poses of the first 10 frames are the closest. It has the largest pose difference at frame 31. Volleyball players need to make the corresponding posture correction in combination with the joint angle trajectories.

Human posture monitoring is the most important part in volleyball auxiliary training. It obtains human body posture information from video or image sequences,

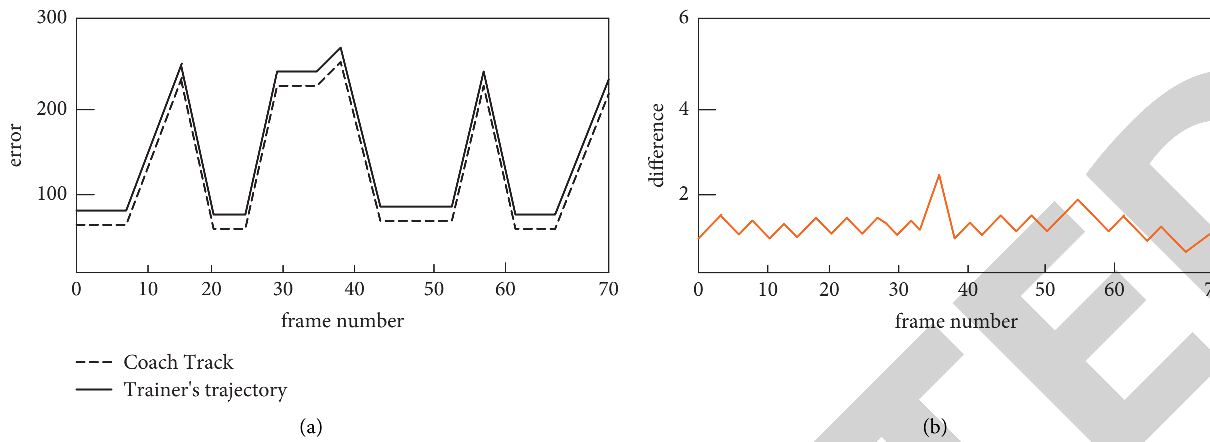

Figure 9: Comparison of joint angles and changes in motion pose similarity. (a) Comparison of joint angles. (b) Motion pose similarity change graph.

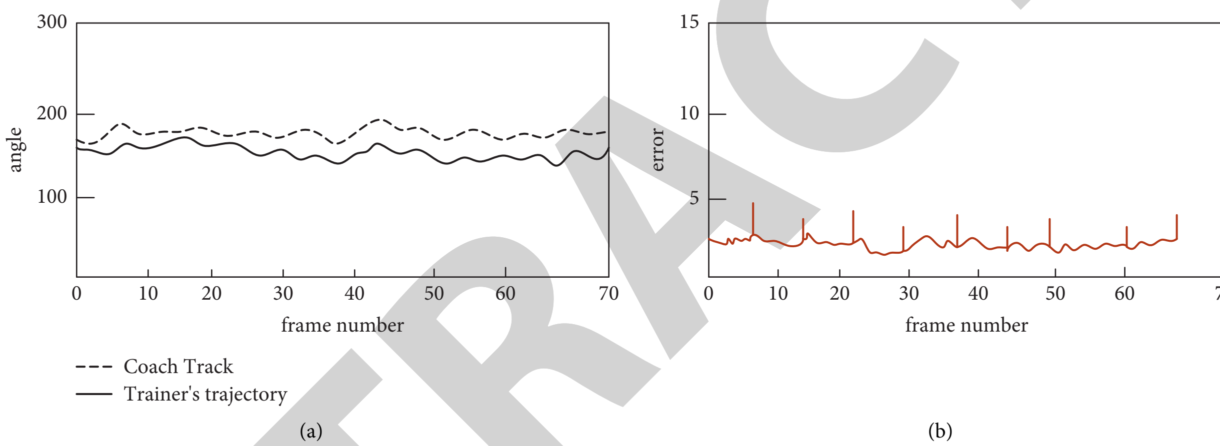

Figure 10: Joint and angle difference curves for volleyball coaches and players. (a) Comparison of joints between volleyball coaches and players. (b) Angle difference graph.

analyzes and summarizes motion posture, and establishes posture auxiliary indicators, as shown in Figure 10.

As shown in Figure 10, it shows that, in the whole volleyball movement, the movement of the arm plays a leading role. It finds that, by comparing the angles of each joint in each frame, motion corrections can be made. Target detection, pose estimate based on human silhouette edge features mixed with image processing, and other methods are used to gather the swing attitude data of trainers and instructors. Finally, as an output, it uses two supplementary indicators: joint angle trajectory and posture similarity.

5. Conclusions

Due to the lack of professional teachers in grass-roots volleyball education, most players do not have the opportunity to obtain one-on-one personal coaching guidance. This results in that students cannot get timely and effective reminders when there is a major problem with their movement posture during training or self-practice. This paper aims to meet the demand for real-time monitoring of dribbling posture during volleyball training and proposes the monitoring of volleyball posture based on machine learning in the context of artificial intelligence. This allows athletes to discover their own mistakes and correct them in time. This paper introduces the human posture monitoring algorithm in detail and briefly explains the necessity of machine learning in volleyball, to expand the discussion of the full text. In the experimental part, this paper compares the proposed algorithm with the other three methods. Finally, it is found that the algorithm in this paper is more accurate in detecting the movements of athletes than the other three algorithms. The error is smaller, and the wrong posture of the athlete can be corrected in time. In the experimental part, the auxiliary training based on pose similarity is analyzed. After conducting experiments on the movements of five volleyball players, it was found that the posture monitoring algorithm based on machine learning is beneficial for volleyball players to improve their own skills. Because the author's own knowledge is weak, this article still has many shortcomings in the experimental part, but the author will continue to work hard to continue to improve.

Data Availability

The data underlying the results presented in the study are available within the manuscript.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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