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Research Article

Attitude Perception of Badminton Players Based on Mobile Edge Computing

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In order to help badminton players make reasonable training plans and realize a comprehensive grasp of the training process, this paper mainly recognizes and perceives the posture of badminton athletes based on the method of moving edge calculation. Firstly, from the perspective of moving edge motion analysis, considering the vector field formed by moving edge vector as movable spatial distribution information, the spatial distribution model of moving edge field is realized. Secondly, while athletes interact with the computer through limb movement, the overall posture of athletes is divided into several parts, and each part is perceived separately. Finally, in the human posture evaluation module, an algorithm for human posture evaluation in the image pixel plane is proposed. Through comparative experiments, the motion recognition algorithm can effectively recognize the three typical swing movements of badminton players in the video and improve the overall performance of the existing recognition algorithms.

1. Introduction

Collecting data in sports and analyzing the data to complete posture perception is a hot spot in the intellectualization of the sports industry in recent years. In badminton competitions, athletes' attitude perception information can become an important semantic clue to understand the competition process, discover technical details, and extract highlights [1, 2]. In terms of the fineness of visual content analysis, the movement trajectory information of badminton players can be regarded as a coarse-grained description, which is the macroperformance of the whole game. The attitude perception of badminton players can be regarded as a fine-grained description, which can embody the details of the game [3, 4]. In order to analyze and understand sports video content in more detail, it is necessary to identify athletes' actions and collect the training information and posture information of athletes, so as to reasonably formulate the training arrangement [5]. On the basis of a large number of data analyses, we can realize a comprehensive grasp of the sports training process.

There are two main research directions of attitude perception. One is attitude perception based on inertial sensors. For example, in literature [6], three-axis acceleration sensors are used to collect user action data, and gesture recognition is realized for time-series modeling based on the Hidden Markov model. Literature [7] uses principal component analysis to perceive human posture based on the data collected by the three-axis acceleration sensor. The other is to use video surveillance and image processing for gesture perception. For example, in [8], for the complex environment, depth image technology is used for gesture recognition, and the average recognition rate of gesture can reach 98.4%. In racket motion recognition based on image and video data acquisition, [9] established an event hiding Markov model with binary classification according to the position of players on the court. Literature [10] proposed a badminton game data mining method based on two-dimensional sequence images. Literature [11] classifies the badminton shot of the compressed video and identifies the type of attack ball by detecting the badminton trajectory. Among the research topics based on badminton, most of them focus on the relationship between racket speed and ball speed, the prediction of ball speed, and the monitoring of players' state characteristics. There are few studies on the detection, analysis, and training of controlled steps for the classification, recognition, and training of hitting movements. The hitting action and controlled step are two important parts of badminton technology. By analyzing different hitting actions and comparing the hitting action characteristics of athletes with different technical levels, it is an important way to improve badminton skills.

This paper will take badminton game video as the research object to track and recognize the badminton players' swing in time-series images. Based on the idea of local motion vision analysis and grid classification, this paper proposes a motion descriptor based on moving edge calculation and constructs an athlete's attitude perception and evaluation algorithm to classify and recognize three typical swing movements of badminton players [12]. The first part is the introduction, which mainly introduces the research significance and research status at home and abroad. The second part is the swing motion perception based on moving edge calculation, which mainly focuses on the perception, segmentation, and recognition of badminton players' swing motion. The third part is the posture evaluation of badminton players, which mainly evaluates the perception of human posture, which helps athletes improve the standard of movement. The fourth part is the experimental results and analysis, and the fifth part is the summary and prospect of the full text.

2. Swing Motion Perception Based on Moving Edge Computing

Athletes' three-dimensional posture perception technology is the basis of realizing sports training auxiliary systems. In order to carry out a three-dimensional simulation of athletes' movement posture, so as to adjust the training mode and improve the training level, this paper studies the application of the unmarked three-dimensional posture perception method in a training assistant system [13, 14]. While the athletes interact with the computer through limb movement, they adopt the method of partial estimation, that is, the athletes' overall posture is divided into multiple partial postures, and each part is perceived separately. Then, the overall posture is generated from part of the posture, so as to realize the estimation of athletes' sports posture. The algorithm block diagram is shown in Figure 1. It includes an action segmentation module and pattern recognition module. The purpose of the action segmentation module is to segment the action interval of the original data, so as to extract the data of a single action of athletes, including signal selection, smoothing processing, and segmentation point acquisition.

2.1. Mobile Edge Computing. Based on the machine learning [15–17] methods, a descriptor describing different types of motion is proposed after calculating the moving edge features of the player tracking image time series. The key to using moving edge computing is that the features obtained from a large number of noisy videos are extremely inaccurate. In the process of visual analysis using moving edge calculation, moving edge is considered as the timing displacement information of each pixel in the video frame, which puts forward higher requirements for the accuracy of moving edge calculation [18]. In order to make effective use of the moving edge features of a large number of noisy moving videos, we start with the analysis of the moving edge field and consider the vector field formed by the moving edge vector as movable spatial distribution information. Then, with the help of the motion descriptor of compact expression, the robustness of these features is enhanced. The movement of these images is the result of the relative displacement of the athlete's limbs and trunk. These relative motions are represented in different regions of the tracking image [19]. These local features can not be effectively expressed by global features. At present, we can use the local analysis technology based on grid classification to divide the moving edge field of the adjusted image into nonoverlapping subdomains. Each subfield is called a grid. Through the histogram statistics of each grid, the spatial distribution model of the moving edge field can be realized.

The moving edge feature based on the tracking image can only reflect the motion information of athletes in the image foreground, and the background in the tracking image will affect the moving edge calculation. Therefore, it is necessary to clear the background. Considering the uniform characteristics of the background color of the sports field, it is necessary to adopt the modeling method based on the Gaussian mixture model and use the region growth algorithm for postprocessing to obtain the athletes with global foreground [20].

The light field can be estimated by adjusting the image sequence according to the player with clear background. However, considering the following points, it is necessary to use the difference between adjacent tracking images to calculate the light field. Firstly, the brightness of the athlete's tracking image will be different due to the changes of camera flash and light intensity in the stadium. This difference will lead to incorrect moving edge calculation [21]. Therefore, it is necessary to use image difference calculation to eliminate the influence of brightness change. Secondly, the academic findings of the biological vision system show that human visual cells are more sensitive to the direction and speed of object edge movement. Therefore, the moving edge calculation based on image difference can better reflect the mechanism of the human visual system's response to object motion. Based on the differential image, the horn Schunck algorithm is used to estimate the moving edge field of the player tracking image. The whole calculation process can be formalized as

$$\begin{aligned} \mathrm{EI}_k &= \mathrm{ID}_k - \mathrm{ID}_{k-1}, \\ \mathrm{Mov}_k &= G\left(\mathrm{EI}_k\right) + \delta. \end{aligned} \tag{1}$$

In the equation, EI_k is the tracking image ID_k and ID_{k-1} differential image. Mov_k is the calculated mobile edge field. K is the number of image sequence alignments.

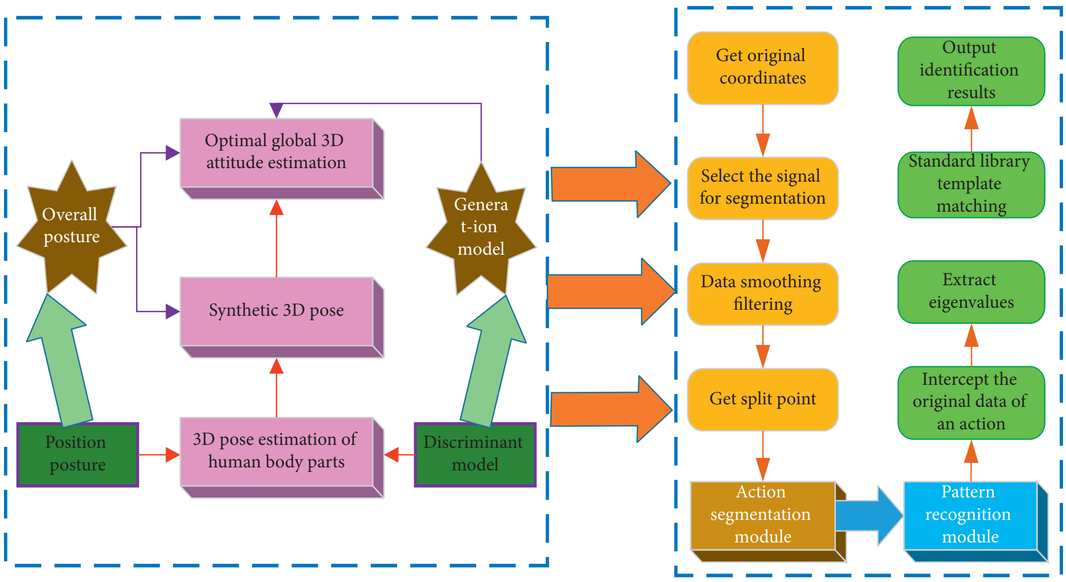

FIGURE 1: Estimation process of motion attitude.

2.2. Swing Motion Segmentation

2.2.1. Action Segmentation Algorithm. The action segmentation algorithm is used to separate the athletes' actions in a period of time and get the starting point and endpoint of each action. The accuracy of the motion segmentation algorithm will directly affect the accuracy of motion recognition and motion counting. The action segmentation algorithm used in this paper can segment continuous complex actions, which is helpful to improve the accuracy of action recognition and counting.

The motion segmentation algorithm needs to select a signal with relatively large signal amplitude and relatively few local peaks and troughs from the nine signals of x-, y-, and z-axis acceleration, angular velocity, and attitude angle. This is conducive to removing local peaks and troughs in later smoothing filtering and improving the accuracy of action segmentation. Since the three-axis attitude angle signal range is -180° to 180°, when the attitude angle exceeds 180°, the signal will suddenly change to -180°, which is easy to misjudge the peak and trough, so only the waveforms of three-axis acceleration. Figure 2 reflects the six signal waveforms of acceleration and angular velocity when athletes continuously perform table tennis forehand action. It can be found that the number of local peaks of the z-axis in an action cycle is relatively small and the amplitude is large, which is more suitable for limited smoothing processing. The arrow in the figure indicates the acceleration signal direction of each axis of the MEMS sensor, and the angular velocity direction of each axis conforms to the spiral law of the right hand of the human body. When the human body performs swing, walking, and running, the arm tends to rotate around the z-axis. After that, the signals of various axes of badminton forehand, walking, running, and other movements are compared. The z-axis angular velocity signal can still reflect good separability. Therefore, this algorithm uses this signal as the segmentation signal.

The diamond represents the peak and trough, and the circle represents the zero point. The smoothed waveform makes it easier to find the signal peak, trough, and zero point by using the program, and the left and right adjacent zeros as the starting point or endpoint are trough and peak, respectively. In order to further reduce the local peaks and troughs caused by action details, this paper adds the minimum threshold Tmin of action interval on the time axis. It is generally considered that the fastest completion time of action of the human body is 0.2 s. All zeros occurring in this time period will be removed; otherwise, the recognition error rate and counting error times will be increased. Therefore, Tmin is selected as 0.2 s. By using the human body detector to detect the position of the player in the badminton swing video segment, the position of the player in the video frame is detected and marked with a rectangular box. Then, only the feature points in the inner region of the rectangular box are detected, and the feature points detected in the region are tracked. In this way, the position information of the trajectory in the video frame not only can be obtained, which reduces the amount of computation of the algorithm, but also excludes the motion trajectory in the other unwanted background, which effectively increases the robustness of the algorithm.

2.2.2. Eigenvalue Extraction. The average resultant acceleration a is the average value of the resultant triaxial acceleration signal of action. The formula is as follows:

$$\overline{\mathrm{Acc}} = \frac{\sum_{i=1}^{N} \mathrm{Acc}_i}{N}. \tag{2}$$

N is the number of sampling points of action. Composite acceleration variance σ^2_{Acc} is as follows:

$$\sigma^2_{\mathrm{Acc}} = \frac{\sum_{i=1}^{N} \left(\mathrm{Acc}_i - \overline{\mathrm{Acc}}\right)^2}{N}. \tag{3}$$

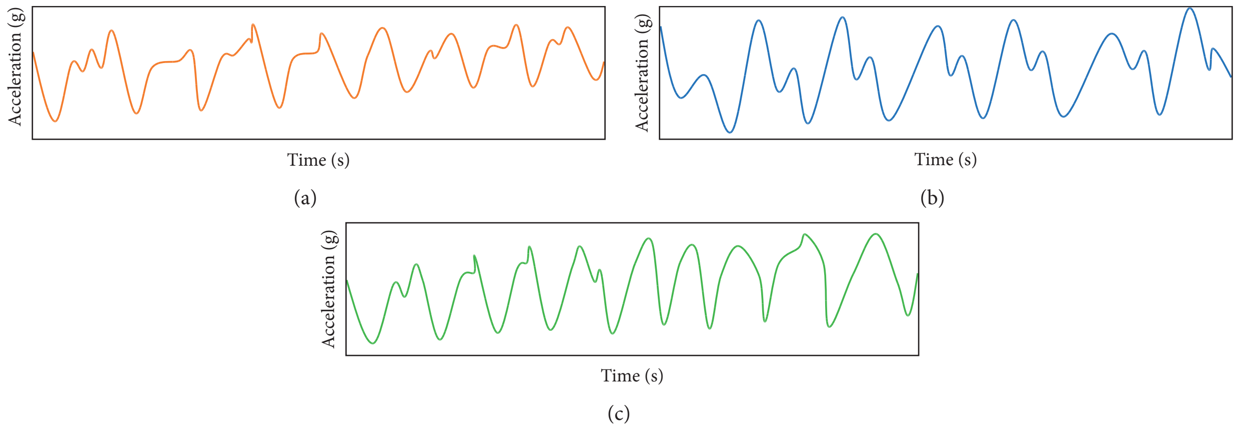

Figure 2: Comparison of acceleration signal waveforms of each axis.

The peak and valley value of synthetic acceleration Acc_{pv} is as follows:

$$\mathrm{Acc}_{pv} = \mathrm{Max}(\mathrm{Acc}) - \mathrm{Min}(\mathrm{Acc}). \tag{4}$$

The average synthetic angular velocity is ω. The average value of the synthesized three-axis angular velocity signal of an action is calculated as follows:

$$\overline{Av} = \frac{\sum_{i=1}^{k} Av}{K}. \tag{5}$$

Composite acceleration variance σ_{Av}^2 is as follows:

$$\sigma_{Av}^2 = \frac{\sum_{i=1}^{N} \left(Av_i - \overline{Av}\right)^2}{N},$$
$$Av_{pv} = \mathrm{Max}(Av) - \mathrm{Min}(Av). \tag{6}$$

The formula is as follows:

$$\mathrm{Cov}(\mathrm{Acc}, Av) = \frac{\sum_{i=1}^{k} \left(\mathrm{Acc}_i - \overline{\mathrm{Acc}}\right)\left(Av_i - \overline{Av}\right)}{(k-1)}. \tag{7}$$

The attitude angle changes ϕ_x, ϕ_y, and ϕ_z of x, y, and z axes are expressed by the following equations, respectively.

$$\phi_x = \sum_{i=2}^{k} \left|\omega_{x,i} - \omega_{x,i-1}\right|,$$
$$\phi_y = \sum_{i=2}^{k} \left|\omega_{y,i} - \omega_{y,i-1}\right|, \tag{8}$$
$$\phi_z = \sum_{i=2}^{k} \left|\omega_{z,i} - \omega_{z,i-1}\right|.$$

2.3. Recognition of Swing Movement. As described above, the movement of the athlete in the adjustment image is caused by the relative displacement in his body, and these movements exist in the corresponding image area. For different gestures, the spatial distribution of the moving edge field is different. The whole process of swing recognition includes data acquisition, window interception, feature extraction and selection, and recognition algorithm research. In Figure 3, the moving edge vector of the image of the up swing racket is densely distributed in the upper part of the image. In the normal image of the left swing of the racket, the moving edge field on the left is more concentrated than that on the right. In contrast, in the image of the right swing racket, the right side is denser than the left side. The usual action recognition methods only use the distribution characteristics and characterize them based on the idea of local analysis. In this paper, an effective region division method is proposed, which is called mesh division.

The moving edge field after smoothing and denoising is divided into nonintersecting grid regions in the vertical and horizontal directions of the adjusted image. Theoretically, meshing can be constructed in any spatial form. Specifically, the number of vertical and horizontal grids is random. However, considering the adjustment of the player's body structure and computational complexity in the image, we use $3 * 3$ grid segmentation. Too simple partition model cannot give a complete description of the spatial distribution of moving edges. However, too complex partitions such as $5 * 5$ and $7 * 7$ will reduce the grid area, so it is estimated that the histogram of moving edges will become sparse. A dense trajectory algorithm can be selected as the basic algorithm for badminton swing recognition, and then, optimization measures are proposed on the basis of this algorithm, so that the algorithm can recognize badminton swing more effectively.

Its main principle is to identify the pixels with an obvious color change or brightness change in the digital image. The significant change of these pixels often represents the important change of this part of the attributes of the image, including discontinuity in depth, discontinuity in direction, and discontinuity in brightness. Based on the kernel density estimation of color layout and the grid histogram of direction gradient, a moving edge histogram based on grid division is developed as the motion descriptor of player swing. For an optical vector with coordinate P in a given moving edge field, its horizontal and vertical components are $H_x(r)$ and $H_y(r)$, respectively. Then, use equation (2) to define the amplitude $N(r)$ and the direction angle $\delta(r)$:

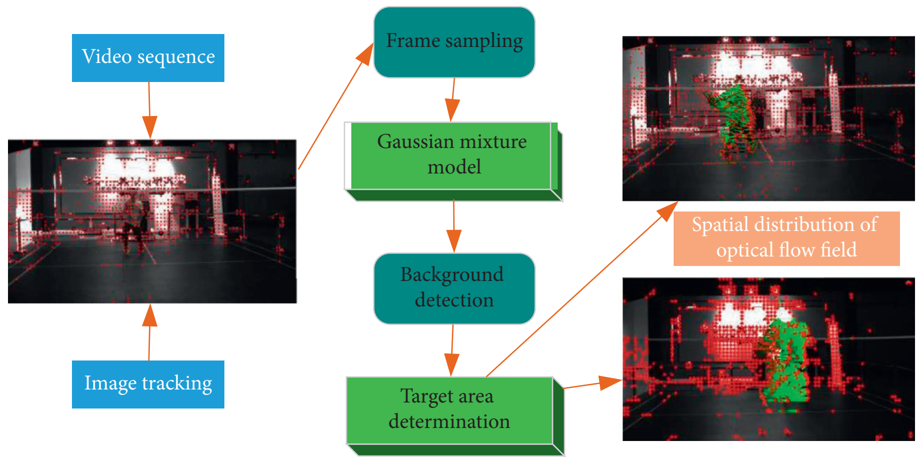

Figure 3: Distribution of movement edge field of athletes.

$$N(r) = \sqrt{H_x^2(r) + H_y^2(r)},$$
$$\delta(r) = \arctan\left[\frac{H_x(r)}{H_y(r)}\right]. \tag{9}$$

The main idea of grid division based on moving edge histogram is that for each grid region, the moving edge vector of any coordinate r is the angle after $N(r)$ weighted quantization $\delta(r)$ of the magnitude. The quantization weighting strategy not only considers its own amplitude $N(r)$ but also uses the kernel density estimation method to consider the distribution information of adjacent moving edge vectors.

Using the existing sports posture database C, the sports posture sample set D can be obtained through classification. For the new athlete posture image, the athlete's posture can be determined only by looking for the sample with the maximum probability of $p(y|z)$. X represents the posture state variable of a specific part, and Z represents the posture state variable of the athlete's posture image.

First, we take $p(y|z)$ as the edge distribution of motion attitude sample set D; then,

$$p(y|z) = \sum_i p(y|z, D)p(D), \tag{10}$$

where $p(y|z, D)$ is used to represent the position posture state variable x; that is, it conforms to the athlete's observed posture state variable Z. At the same time, it belongs to the probability of motion attitude sample library D.

Assuming that the position attitude state variable x and the motion attitude sample library D are independent of each other, there are

$$p(z|y, D) = \frac{p(z|y)p(z|D)}{p(z)}. \tag{11}$$

Then, the equation can be changed to

$$p(y|z) = p(z|y)\sum_i p(z|\mathrm{D})p(y, D)p(D). \tag{12}$$

It is assumed that all attitude samples in the attitude sample library are evenly distributed, and the probability of p (D) is uniform. Then, the posterior probability can be simplified as

$$p(y|z) = p(z|y)\sum_i p(z|\mathrm{D})p(y, D). \tag{13}$$

After classification, the set of samples in category D can be reasonably regarded as Gaussian distribution; that is, it meets the following requirements:

$$y|D \sim N(\mu, Z). \tag{14}$$

μ and Z are the probability mean and covariance of the sample in the motion attitude sample set D. Then, the probability of occurrence of posture state variables on the athlete's posture image is

$$p(z|D) = \int p(z|y)p(y|D). \tag{15}$$

For the Monte Carlo approximate calculation of equation (5), firstly, the probability p $(x|c)$ needs to be sampled and calculated. Then, the confidence $p(z|y)$ of each sampling point is calculated. Finally, the weighted sum of the confidence of all sampling points is obtained.

Then, according to the above equation (4), under the condition of giving the athlete's posture state variable z, the posterior probability $p(y|z)$ can be calculated for each sports posture example y in the sports posture database D. Through this value, we can judge the similarity between the athlete's current posture and the sample posture in the database, so as to estimate the athlete's posture. In order to put forward the shortcomings of the action to be analyzed in the execution process, we need to get the difference between it and the standard action.

3. Posture Evaluation of Badminton Players

In the process of badminton players' movement, there are high requirements for the standard degree of their own actions, but in training, they always rely on the coach's correction of badminton players' posture, and there is no more accurate evaluation system. After analysis, the human posture evaluation system designs an algorithm: take a group of bone point coordinates of badminton players in the camera coordinate system in a single frame image as input, compare it with the badminton players' standard posture library from the same perspective, and then calculate the matching standard posture and cumulative error. The cumulative error reflects the similarity with the matched standard attitude. The lower the cumulative error, the higher the similarity.

3.1. Human Posture Evaluation Algorithm

3.1.1. Algorithm Flow. The overall flow of the human posture evaluation algorithm is shown in Figure 4.

The specific process is as follows:

(1) Coordinate conversion is performed on the coordinates of human bone points conforming to the 13 point human posture model, the image pixel coordinate system is converted to the rectangular coordinate system with point 0 as the origin, and the vectors from the coordinates of each human bone point to point 0 and the included angle between the vectors and the bone points formed in the positive direction of the x-axis of the rectangular coordinate system are calculated, respectively.

(2) Set the priority of each bone point, take one bone point in sequence according to the priority, calculate the cumulative difference with the corresponding bone points of all pose models in the candidate pose set, and output the cumulative difference. After all bone points of the pose model to be measured are calculated, enter step (3). Wherein, the cumulative difference is the absolute value of the difference of the included angle of the bone points in step (1), and the candidate posture set is initially a preset human posture standard library.

(3) Calculate the cumulative error, find the attitude model with the smallest cumulative error in the candidate attitude set, and output the serial number of the attitude model and the cumulative error. The cumulative error is the sum of the cumulative differences of each bone point in the attitude model of the attitude model to be measured in a candidate attitude set.

3.1.2. Algorithm Analysis. At present, the mainstream human posture evaluation algorithms are human posture evaluation in the world coordinate system. The conversion from camera coordinate system (image pixel coordinate system) to world coordinate system requires a depth camera. At the same time, there is an origin (0,0,0) in the conversion process. By comparing the vector set of human postures in the world coordinate system, we can achieve real-time tracking and evaluation of human posture.

This algorithm is different from most current human pose evaluation algorithms. Although it is more comprehensive to evaluate human pose in three-dimensional space, the cost of methods such as depth camera and binocular vision to supplement the missing information in the conversion process is too high. Therefore, this algorithm matches the human posture with the standard posture library under the image pixel coordinate system, so as to obtain the evaluation results, and makes the standard human posture library (forehand, backhand, and jump ball) in badminton for testing.

The evaluation part of the human pose evaluation algorithm has three steps: (1) coordinate transformation of the input bone point coordinates, (2) matching with the standard attitude library, and (3) matching result processing.

In the image pixel coordinate system, the change of human posture coordinate set is not only affected by the position of badminton players on the badminton court (such as front and rear half-court, left and right half-court) but also affected by the camera model, so it can not be directly matched with the standard posture. If we want to match the human posture coordinate set, the above two problems must be solved. The idea of this algorithm is to transform the input coordinates. The transformation steps are mainly divided into two steps, as shown in Figure 5.

The transformation step (a) is carried out because the athletes' different positions on the badminton court will lead to problems in matching with the standard posture. Even if a certain posture appears in different positions on the badminton court, it will show different coordinates in the camera perspective. Therefore, this algorithm puts forward an idea: convert the input coordinate system to the coordinate system composed of the athlete's own human body, so that the positions of the other 12 bone points are determined relative to the neck point. Regardless of the standard posture or the input athlete posture, the neck point is the origin, which can eliminate the problems caused by different positions.

The reason for performing the transformation step (b) is that there are differences between individual body shapes, which will lead to uncertain matching results even if each individual makes the same posture. Therefore, based on the "cosine similarity," the (b) transformation step is proposed: transform the image pixel coordinate system into a rectangular coordinate system with the neck point as the origin, and solve the included angle between the vector formed by the other points and the origin and the positive direction of the x-axis, in order to eliminate the uncertainty caused by this individual difference.

3.2. Matching Human Posture with Standard Library. In the human posture evaluation system, the human standard posture database is also an important index. If the human body standard posture itself is not standardized, the accuracy of human body posture evaluation cannot be guaranteed. Due to the complexity of modeling and the continuous improvement of the effect of deep learning, human posture estimation has gradually focused on deep

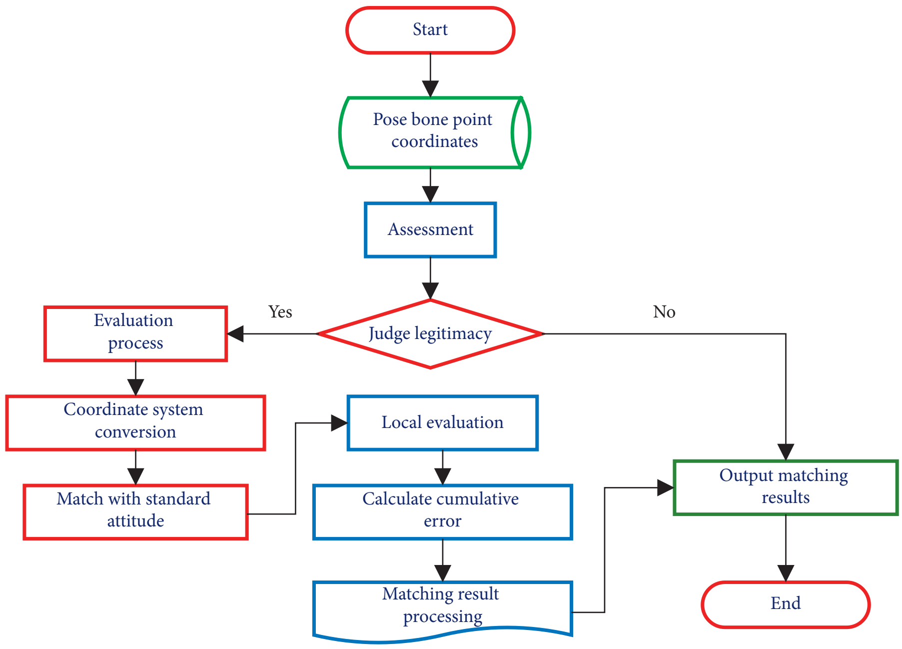

Figure 4: Human posture evaluation algorithm flow.

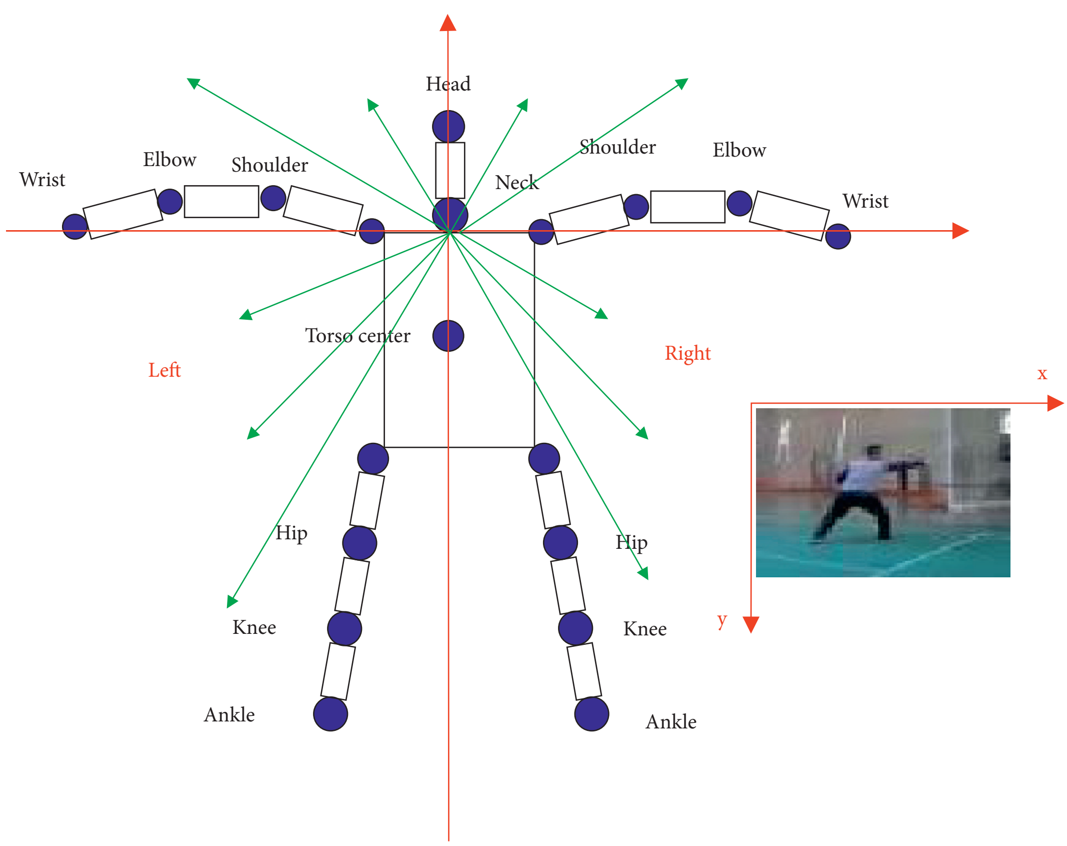

Figure 5: Bone point coordinate system.

learning, but estimation speed and ReLU optimization are still a new challenge. Therefore, in order to show the effect, this algorithm selects three actions: forehand pick, backhand draw, and jump ball, so that an athlete can make a standard posture first and then calculate the parameters of the standard posture of the human body through the process shown in Figure 6. Calculate the similarity between the action and the standard action of this kind of action, and

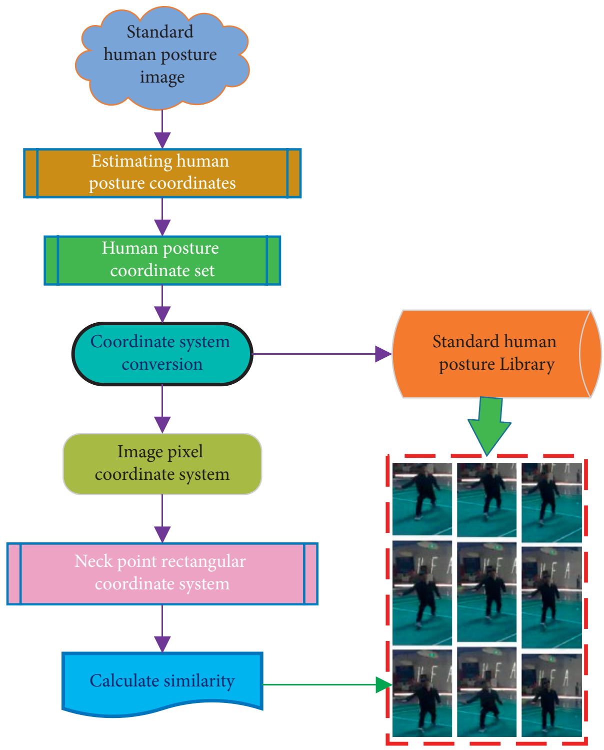

Figure 6: Production process of standard human posture library.

then use the scoring formula to calculate the score of the action through the similarity.

After the coordinate transformation of the rest points in the human posture model, the serial number is readjusted. The right upper limb area contains three bone points: right shoulder, right elbow, and right wrist. The adjusted coordinate numbers are 0, 1, and 2. The left region of the upper limb contains three bone points: left shoulder, left elbow, and left wrist. The adjusted coordinate numbers are 3, 4, and 5. The right area of the lower limb includes three bone points: right hip, right knee, and right ankle. The adjusted coordinate numbers are 6, 7, and 8; The left area of the lower limb contains three bone points: left hip, left knee, and left ankle. The adjusted coordinate numbers are 9, 10, and 11.

The overall matching process is divided into 9 small stages, matching 0, 1, 2, 6, 7, 8, 9, 10, and 11 areas, respectively. The of each small area is to take the corresponding angle between the attitude to be evaluated and the candidate standard pose in the previous stage and calculate the absolute value of the difference between them, which is later called cumulative error. If the cumulative error is less than or equal to the allowable error of this stage, the standard pose of the human body conforms to the evaluation of this stage, and the standard pose is put into the candidate standard pose set of this stage.

There are two possible evaluation results in this process: (1) if the angle of the pose to be evaluated in this stage is the loss angle due to the absence of the bone point in the input), the candidate standard pose set in this stage is the candidate standard pose set in the previous stage, that is, skip this stage. (2) After all matching is completed, if there is no candidate standard pose set in this stage, the comparison output result is directly ended. The output results include all the standard poses matched, the stage at the end of matching, and the loss caused by the accumulation of accumulated errors in the matching process.

After the human posture evaluation algorithm, there are two output results: one is the most appropriate standard human posture sequence number, and the other is the similarity with the matched standard human posture, expressed by loss. The matching results obtained in the human posture evaluation algorithm also need to be processed.

If "−1," "0", and "1" appear, this indicates that the comparison of the left area of the upper limb is not completed, and "matching failed" is output. Because the key point of a badminton player's posture matching is the left area of the upper limb, it represents the badminton player's racket holding posture, which is the key area to judge whether the badminton action is standard or not. If "matching failure" occurs, it indicates that the posture of the athlete in the frame image does not conform to any posture in the standard library.

If other information appears, the matching result has appeared. The higher the sequence number, the better the matching result. The loss reflects the similarity between the standard posture meeting the matching conditions and the human posture to be matched at the same stage. The lower the loss, the higher the similarity. How to introduce this feedback into the process of human posture evaluation is still the focus of follow-up work, and it is also a breakthrough for human posture evaluation algorithms to improve the accuracy of evaluation.

How to introduce this feedback into the process of human posture evaluation is still the focus of follow-up work, and it is also a breakthrough for human posture evaluation algorithms to improve the accuracy of evaluation. In the follow-up research, we not only need to get the similarity between the action to be analyzed and the standard action but also give the differences between them, so as to provide the basis for the subsequent correction opinions of the action to be analyzed.

4. Experimental Results and Analysis

We used badminton competitions from radio and television programs and the London Olympic Games. Video is stored in MPEG-2 compressed format, and the size of the video frame is $352 * 288$. The types of different swings in these competitions are marked in manual mode. The real value is created in the ground truth, as listed in Table 1 and Figure 7, including the game name, player, video time length, and the number of three swings.

In order to quantitatively evaluate the algorithm, three evaluation indexes are defined in this paper. Firstly, recall rate (R) and accuracy rate (P) are defined to determine the recognition ability of each swing.

4.1. Action Recognition Results. For the badminton video data shown in Table 1, a classifier is trained to judge the players' actions. All data use the three times cross-validation strategy to form the training set and test set, that is, 2/3 of the data are used as training samples, and the rest are test samples. After three iterative tests, the average of the three evaluation data is considered as the final result. Table 2 shows the experimental results of the algorithm. The experimental comparison results of action recognition are shown in Figure 8.

It can be seen from Table 2 that, for badminton competition, the methods proposed in this paper have good recognition accuracy, which can reach 87.6%. In the test video, the moving image has 30~40 pixels. Due to factors such as low-quality video and camera movement, the swing action is not obvious in every detail. The above research results confirm that the proposed motion descriptor and recognition strategy are very effective. In the experiment, the recognition error of swing movement occurs because high-level athletes will use some unconventional swing techniques to hit a difficult return ball in the game. The optical flow field distribution of these abnormal swing movements is different from the normal situation, so the moving edge histogram based on grid division cannot accurately describe these movements.

4.2. Attitude Perception Analysis. While evaluating the motion recognition method based on motion analysis, the effectiveness of the method based on motion pose feature analysis and the recognition method in this paper is compared. The method based on motion posture feature analysis is to track the athlete's action trajectory to obtain the target area. The contour of athletes' action posture is obtained by processing the background, and the action contour information is mapped into a feature space by Karttunen Loeve (KL) transform. Then, the eigenvalues are arranged in descending order, and the eigenvector of the first m maximum constitutes the apparent descriptor of action and gesture. Finally, the nearest neighbor classifier is used to recognize the action sequence according to these descriptors. As in the above experiments, three cross-validation strategies are applied to separate all data into the training set and test set. In the experiment, the structure of the action descriptor is simplified by modifying and selecting the percentage of the sorted apparent vector. The data set used here achieves the best accuracy when the first 80% of the view vectors are selected. The evaluation results based on the action attitude feature analysis method are shown in Table 3. The effect comparison is shown in Figure 9.

It can be seen from Table 3 that the method proposed in this paper is better than the feature analysis method. This is because this method cannot effectively distinguish the changes of camera angle or athlete's working direction in sports video, so the descriptor based on action posture contour reconstruction does not have excellent classification

Table 1: Experimental data of motion recognition.

Game video clip	Up swing times	Left swing times	Right swing times
Olympic games	52	102	147
Masters	251	398	289
Sudirman cup	218	368	378
Open tournament	239	147	191
Total	760	1015	1005

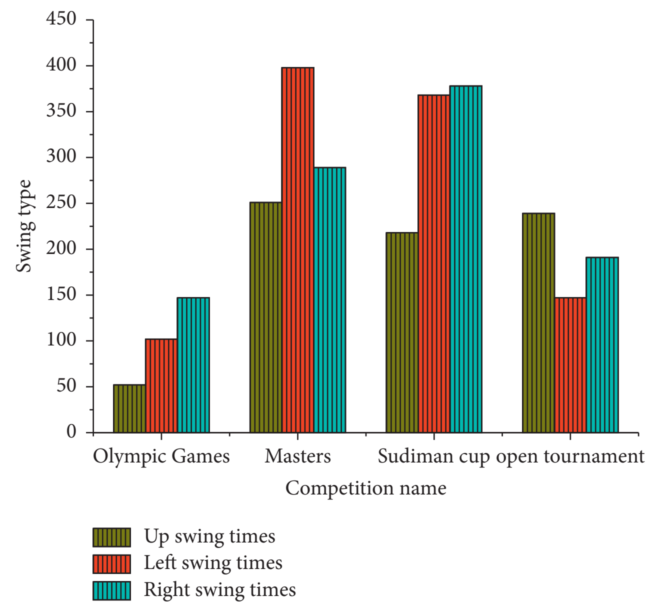

Figure 7: Experimental data display.

Table 2: Experimental results of motion recognition.

Action classification	Action times	Recall rate (%)	Accuracy rate (%)	Accuracy (%)
Up swing	267	88.7	86.5	
Left swing	148	86.6	92.4	89.2
Right swing	181	90.5	93.8	
Average	596	88.5	89.9	89.2

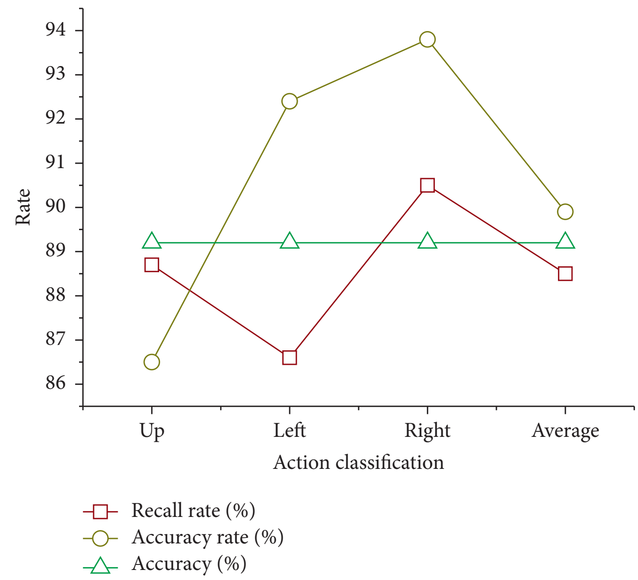

Figure 8: Experimental comparison of motion recognition.

Table 3: Experimental results based on feature analysis.

Action classification	Action times	Recall rate (%)	Accuracy rate (%)	Accuracy (%)
Up swing	267	58.4	63.4	
Left swing	148	65.1	76.2	64.35
Right swing	181	58.7	67.8	
Average	596	60.7	68	64.35

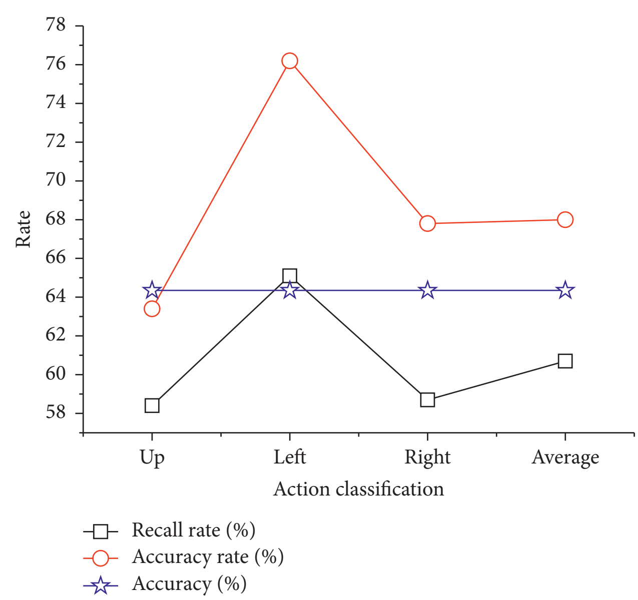

Figure 9: Comparison of experimental results.

Table 4: Record of video frames to be measured and actually measured.

Video name	Number of frames to be measured	Measured frames	Detection rate
Video 1	46	32	0.6956
Video 2	45	43	0.9555
Video 3	132	88	0.6667
Video 4	65	43	0.6615
Video 5	34	26	0.7647
Video 6	51	45	0.8823

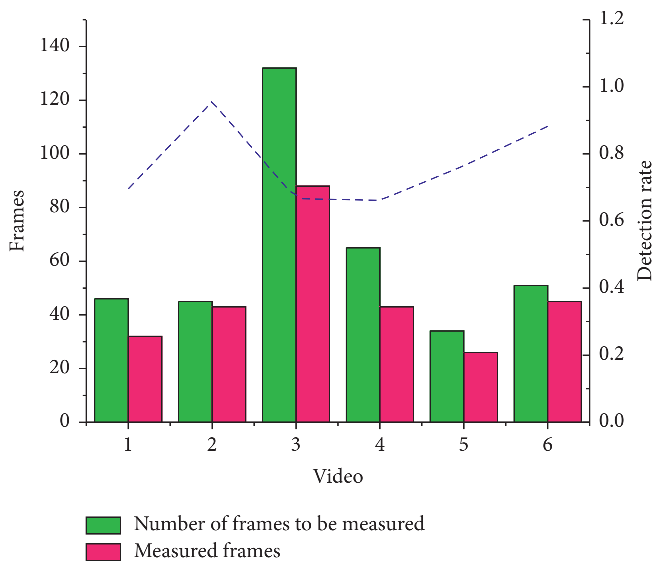

Figure 10: Comparison between the number of frames to be measured and the number of frames actually measured in the video.

robustness. Through comparison, it can be concluded that the motion descriptor in this paper is much better than other motion descriptors in robustness.

Six videos are used for the human posture evaluation module to count the number of frames of posture that should be detected in each video, which is called "frames to be measured." Counting the number of frames of attitude actually detected in each video is called "measured frames." The data comparison is shown in Table 4 and the effect comparison is shown in Figure 10.

5. Conclusion

In badminton competitions, athletes' attitude perception information can become an important semantic clue to understand the competition process, discover technical details, and extract highlights. Therefore, this paper studies badminton athletes' attitude perception based on moving edge computing. Taking the badminton game video as the research object, the badminton player's swing action in the time-series image is tracked and recognized. The segmented three-dimensional pose estimation method is adopted to realize the three-dimensional perception of the badminton player's pose. The action segmentation algorithm is used to determine the starting point and endpoint of each action, and the counting function of various actions is realized. A motion descriptor based on edge calculation is proposed, and the audio keyword strategy is used to find the player's swing image. Finally, a group of bone point coordinates of badminton players in the camera coordinate system in a single frame image are used as input. Compared with the standard posture library of badminton players from the same perspective, the matching standard posture and cumulative error are calculated. In the future, we can use the current popular big data and cloud computing-related technologies to build a cloud platform for big data analysis, conduct data mining and data analysis on a large number of players' competition and training data, and analyze the technical advantages and weaknesses of various athletes, so as to improve the technical level of athletes faster.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

All the authors do not have any possible conflicts of interest.

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References

[1] B. Chen, D. Mok, W. C. C. Lee, and W. K. Lam, "High-intensity stepwise conditioning programme for improved exercise responses and agility performance of a badminton player with knee pain," *Physical Therapy in Sport*, vol. 16, no. 1, pp. 80–85, 2015.

[2] H. N. Praja, R. P. Yudha, S. Sundari, and W. A. Nugroho, "Reproductivity and validity analysis of badminton player cognitive performance using badminton reaction inhibition test (BRIT)," *Kinestetik: Jurnal Ilmiah Pendidikan Jasmani*, vol. 4, no. 2, pp. 175–183, 2020.

[3] N. A. Rahmad, N. A. J. Sufri, N. H. Muzamil, and M. A. As'ari, "Badminton player detection using faster region convolutional neural network," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 14, no. 3, pp. 1330–1335, 2019.

[4] M. King, H. Towler, R. Dillon, and S. N. McErlain, "A correlational analysis of shuttlecock speed kinematic determinants in the badminton jump smash," *Applied Sciences*, vol. 10, no. 4, pp. 1248–1261, 2020.

[5] M. Phomsoupha and G. Laffaye, "The science of badminton: game characteristics, anthropometry, physiology, visual fitness and biomechanics," *Sports Medicine*, vol. 45, no. 4, pp. 473–495, 2015.

[6] R. Sharma, "Preferred leadership behaviours of male and female badminton players," *International journal of Science Culture and Sport*, vol. 3, no. 10, p. 73, 2015.

[7] B. S. Kim, S. M. Shin, and H. G. Lee, "The casual relationship between psychological characteristics and game satisfaction of badminton club members's doubles match - actor effect and partner effect by APIM technique," *Journal of, Coaching Development*, vol. 18, no. 4, pp. 41–50, 2016.

[8] C. L. Hung, M. H. Hung, C. Y. Chang, H. H. Wang, C. S Ho, and K. C Lin, "Influences of lateral jump smash actions in different situations on the lower extremity load of badminton players," *Journal of Sports Science & Medicine*, vol. 19, no. 2, pp. 264–270, 2020.

[9] T. Sonoda, Y. Tashiro, Y. Suzuki et al., "Relationship between agility and lower limb muscle strength, targeting university badminton players," *Journal of Physical Therapy Science*, vol. 30, no. 2, pp. 320–323, 2018.

[10] J. H. Kang and J. S. Lee, "The effect of psychological skill ability on perfectionism and ego resilience of badminton players," *Korean Journal of Sports Science*, vol. 26, no. 2, pp. 379–394, 2017.

[11] H. Z. Zeng, W. Y. Meng, P. Sun, and L. S. Xie, "A study of youth badminton players' participation motivation and relate elements∗," *IOSR Journal of Sports and Physical Education*, vol. 04, no. 3, pp. 44–54, 2017.

[12] K. H. Woldendorp, A. M. Boonstra, A. Tijsma, J. H. Arendzen, and M. F. Reneman, "No association between posture and musculoskeletal complaints in a professional bassist sample," *European Journal of Pain*, vol. 20, no. 3, pp. 399–407, 2016.

[13] Y. Ji and S. Ma, "Remote evaluation system of tennis batting action standard based on acceleration sensor," *Security and Communication Networks*, vol. 2021, no. 6, 11 pages, Article ID 9930084, 2021.

[14] Y. Masu and M. Nagai, "Characteristics of lower limb muscle activity during upper limb elevation in badminton players," *Journal of Physical Therapy Science*, vol. 28, no. 9, pp. 2510–2514, 2016.

[15] M. Zhao, Q. Liu, A. Jha et al., "VoxelEmbed: 3D instance segmentation and tracking with voxel embedding based deep learning," 2021, https://arxiv.org/abs/2106.11480.

[16] W. Chu, P. S. Ho, and W. Li, "An adaptive machine learning method based on finite element analysis for ultra low-k chip package design," *IEEE Transactions on Components, Packaging, and Manufacturing Technology*, vol. 11, no. 9, pp. 1435–1441, 2021.

[17] M. Zhao, A. Jha, Q. Liu et al., "Faster Mean-shift: GPU-accelerated clustering for cosine embedding-based cell segmentation and tracking," *Medical Image Analysis*, vol. 71, Article ID 102048, 2021.

[18] H. Yang and H. Yoo, "Relationship between body composition and physical self-concept: focused on badminton players," *Asia Life Sciences*, no. 1, pp. 805–813, 2018.

[19] S. H. Jang, "Retirement circumstances and social adaptation experience in the Re-socialization process of badminton players," *The Korean Journal of Physical Education*, vol. 55, no. 5, pp. 29–41, 2016.

[20] Y. Deng, X. Liu, Z. Zheng, Q. Zhang, and L. Wu, "A new active contour modeling method for processing-path extraction of flexible material," *Optik*, vol. 127, no. 13, pp. 5422–5429, 2016.

[21] R. J. Kind, "Calculation method for circulation control by tangential blowing around a bluff trailing edge," *Aeronautical Quarterly*, vol. 19, no. 3, pp. 205–223, 1968.