

Research Article

Recognition Method of Volleyball Players' Spike and Take-Off Action Based on DTW Algorithm

Fei He¹ and YongHeng Zhang² 

¹Tai Chi Martial Arts College, Jiaozuo University, Jiaozuo, Henan 454000, China

²School of Finance and Economics, Henan Polytechnic University, Jiaozuo 454000, China

Correspondence should be addressed to YongHeng Zhang; zyh1981@hpu.edu.cn

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In order to improve the recognition ability of volleyball players' spike take-off, and thus promote the accuracy of volleyball spike, this article puts forward the recognition technology of volleyball players' spike take-off based on DTW algorithm combined with image recognition technology. The transmission relation model of detail features of volleyball players' spike take-off action images is constructed, and the edge contour features of volleyball players' spike take-off action images are detected and processed by detail wavelet feature decomposition and DWT algorithm. Using prior Atlas knowledge instead of dark primary color, the detailed information and color of the image are obtained. Through the method of filtering and maintaining, the image is guided to filter the details of the input volleyball player's spike and take-off action image. Sobel operator is used to detect the weak edge information of the animation image. In the edge area, high-order moment feature decomposition and wavelet feature separation are used to enhance the details of the volleyball player's spike and take-off action image and detect and enlarge the key action feature points, so as to improve the ability of enhancing and identifying the details of the action feature points of the image. The test shows that this method can effectively solve the noise and error in the process of recognizing the spike and take-off action of volleyball players, reduce the recognition error, and improve the ability to accurately locate the spike and take-off force point.

1. Introduction

Volleyball is a beautiful and fierce sport. Nowadays, volleyball is popular all over the world and is called the second largest ball game in the world. The spiking and catching of volleyball play a key role in volleyball matches. The spiking must be done in the diagonal spiking area to be considered as a good shot. Mastering the spiking of volleyball is of great significance to improving the competition results. Volleyball spiking is a difficult skill to master, and players often have action deviations. It is necessary to recognize the spiking action in real time. Combining with the image visual feature analysis method, a recognition model of the spiking take-off action of volleyball players is established. It can better analyze the action and technical characteristics of volleyball players' spike and take-off recognition items, and provide accurate data support for guiding

volleyball players' spike and take-off training and competition referee [1].

On the basis of analyzing the color and transmission area of the image, and combining with the rough set of the transmission image [2, 3], the enhancement of the details of the action feature points of the spike take-off image of volleyball players is based on the analysis of the depth-of-field characteristics of the spike take-off image of volleyball players, so as to estimate the transmission parameters and visual feature information of the spike take-off image of middle volleyball players, and improve the output stability of the spike take-off image of volleyball players. Traditionally, the detection method of movement amplitude is used to recognize the spike take-off action of volleyball players, but it is not suitable for sports such as the spike take-off action of volleyball players with multi-dimensional features of falling point and rotation. For this reason, related literature has

been improved. Reference [1] proposed a new AR-based feature extraction method for volleyball players' hitting posture. The AR image acquisition model of volleyball players' hitting posture is constructed, the edge contour feature is extracted, the action feature of volleyball players' hitting posture is analyzed, and the image fusion and feature decomposition of volleyball players' hitting posture are completed through the AR visual space reconstruction technology. Using the method of correlation ambiguity detection, the corner features and gray invariant moment features of the image are extracted, and the volleyball players' hitting posture image actions are tracked, recognized, and extracted. However, the algorithm has a large amount of calculations and poor applicability. Reference [4] proposed an optimal recognition method of volleyball player's arm trajectory based on chaos theory. Based on the principle of background difference, the athlete's motion trajectory is detected, the dynamic arm tracking is carried out by using the particle filter of color histogram, and the phase space of the athlete's arm motion trajectory is reconstructed by integrating the chaos theory. The chaotic invariant representing the athlete's arm motion trajectory is extracted from the reconstructed phase space, and the arm motion trajectory with three-dimensional spatial characteristics is transformed into a one-dimensional arm motion trajectory, and completed the optimization recognition of the volleyball player's arm movement trajectory, but the system is prone to nonlinear distortion in the visual perception process of the volleyball player's spike take-off action field technical action characteristic data [5–9].

In view of the above problems, this article proposes a recognition technology for volleyball players' spiking and jumping action based on DTW algorithm. Firstly, the detail feature detection and information collection of volleyball players' spiking and jumping action image are carried out, and then the edge contour feature detection is processed through detail wavelet feature decomposition and DWT algorithm. Finally, in the edge region, the method of high-order moment feature decomposition and wavelet feature separation is used to enhance the details of volleyball players' spike take-off action image and detect and enlarge the key action feature points. The experiments show that this method has superior performance in improving the fuzzy detection and recognition ability of volleyball players' spike take-off action image details.

2. Transmission Relation of Visual Characteristics of Volleyball Spike Take-Off Action Images

2.1. Perspective View of Volleyball Player's Spike Take-Off Action Image. DTW algorithm is used to measure the similarity of two time series with different lengths. The unknown quantity is stretched or shortened until it is consistent with the length of the reference template. In this process, the unknown sequence will be twisted or bent so that its characteristic quantity corresponds to the standard pattern. The basic principle of DTW is to set the time

correction function and match the feature vectors of the reference template according to the path length and matching point parameters. DTW algorithm is to minimize the sum of weighted distances by local optimization. DTW algorithm can effectively identify the spike and take-off action images of volleyball players through constraints. Boundary condition means that the beginning and end of two sequences must match, and the sequence of each part must match. Continuity condition means that many-to-one and one-to-many situations can only match the surrounding time step in the matching process, that is, it is impossible to cross a certain point to match, and it can only be aligned with its own adjacent points. This can ensure that each coordinate appears in the specified path. Monotonicity means there are many paths satisfying the above constraints, so the essence of the problem is that the optimization problem is to find the optimal image recognition path. Based on DTW algorithm, an image recognition model of volleyball player's spike take-off action is established [10–12]. Combined with the detection of detailed features of volleyball player's spike take-off action image, a transmission relationship analysis model of volleyball player's spike take-off action image is established by using fuzzy color feature matching technology. Combined with the detection of optical highlights of volleyball player's spike take-off action image. Wavelet feature decomposition is to analyze the volatility of specific transformation through small waveforms according to attenuation characteristics, and its oscillation form with positive and negative amplitudes can express dynamic characteristics. Wavelet feature decomposition is a localized analysis using the frequency of time and space. Through the expansion and translation operation, the signal function is gradually refined in multi-scale, finally reaching the time subdivision at high-frequency, and then focusing on the dynamic feature details. Wavelet feature decomposition can cover the whole frequency domain, which provides a mathematically complete description for image feature recognition [13, 14]. By selecting appropriate filters, wavelet transform can greatly reduce or eliminate the correlation between different extracted features. Wavelet feature decomposition has "zoom" characteristics, which can use high-frequency resolution and low time resolution in low-frequency band, and low-frequency resolution and high time resolution in high-frequency band, so as to effectively improve the calculation speed of the algorithm. The detailed wavelet feature decomposition and DWT algorithm technology are used to obtain the dynamic feature point distribution of volleyball player's spike take-off action image. To construct the mathematical model of volleyball players' spike and take-off action images is shown in formula (1):

$$H(i) = K(P_n) + \sum_{j \in \Omega} w(i, j)g(j), \quad (1)$$

where in P_n is the pixel distribution dimension of the image, $K(\cdot)$ is the model function, $w(i, j)$ is the iterative weighting function, $g(j)$ is the residual component of the model, Ω is the template matching domain, and j is the feature detection point.

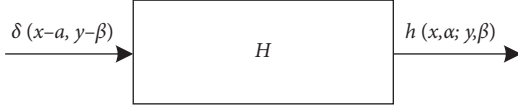


FIGURE 1: Relationship between input and output of image detection.

Taking the boundary pixels of the volleyball player's spike take-off action image as the center, the parameters of the graph model are matched, and the block fusion model of the volleyball player's spike take-off action image is established. The low-pass filter of dark primary color detects that there are some weighted components of pixels in the local area. Based on the prior law distribution of dark channel, the distribution of visual characteristics of volleyball player's spike take-off action image is satisfied as $n \in N(0, \sigma_n^2)$, among which σ_n^2 is the pixel intensity of volleyball player's spike take-off action image is obtained, and the relationship between image detection input and output is shown in Figure 1.

According to Figure 1, a local neighborhood centered on pixel x is constructed, and the invariant moment of dark channel distribution of volleyball players' spike take-off action image under detailed wavelet feature decomposition and DWT algorithm is obtained as shown in formula (2):

$$\begin{aligned} g &= Hf + n, \\ &= \sum_{m=1}^M \sum_{n=1}^N (x - \hat{x})^p (y - \hat{y})^q f(x, y), \\ &= H(l - A)v + n, \end{aligned} \quad (2)$$

where in H is the pixel three-color channel of volleyball player's spike take-off action, f is the fine filtering function, l is the interference intensity of volleyball player's spike take-off action, A is the pixel sequence distribution length of volleyball player's spike take-off action image, \hat{x} is the amplitude of detail distribution, \hat{y} is the X component of pixel depth of field of volleyball player's spike take-off action, it is the Y component of pixel depth of field, and $f(x, y)$ is the detection function.

According to the above analysis, the information collection and pixel sequence analysis model $F = g[H(l - A)v + n]$ of volleyball players' spike take-off action image is established. According to the transmission relationship of volleyball players' spike take-off action image detail features, the image detail features are enhanced by the methods of detail wavelet feature decomposition and DWT algorithm [15], and the perspective image of volleyball players' spike take-off action is obtained.

2.2. Edge Feature Detection and Processing. Knowledge map is an important branch technology of artificial intelligence, and it is a structured semantic knowledge base, which is used to describe concepts and their relationships in the physical world in symbolic form [16]. Its basic constituent units are "entity-relationship-entity" triples, and entities and their related attribute-value pairs. Entities are connected with each other through relationships, forming a network knowledge structure. Knowledge map embedding, as a kind

of prior knowledge, is usually input into many deep neural network models to constrain and supervise the training process of neural networks. Mainstream method of knowledge representation learning: representing entities and relationships as dense low-dimensional vectors realizes distributed representation of entities and relationships, and has become an important method for semantic link prediction and knowledge completion of knowledge map. Prior knowledge of Atlas can significantly improve computational efficiency, effectively alleviate data sparseness, realize heterogeneous information fusion, and help to realize knowledge fusion. The prior map knowledge instead of dark primary color is used, the detailed information and color of the image are obtained, and the gray invariant moments m_{01} and m_{02} of the image are obtained. According to the relative value of the pixel depth of field of the volleyball player's spike take-off action image, the dark channel distribution parameters of the guiding filter are obtained by the method of feature decomposition. Characteristic decomposition is a method of decomposing a matrix into the product of its eigenvalues and eigenvectors. The matrix can be decomposed in a way that shows information that is not obvious in the matrix element arrangement representation. Any real symmetric matrix has characteristic decomposition, but the characteristic decomposition may not be unique. If two or more eigenvectors have the same eigenvalues, then any set of orthogonal vectors in the subspace generated by these eigenvectors are eigenvectors corresponding to the eigenvalues. Therefore, it can be equivalently constructed from these feature vectors as a substitute. Traditionally, matrix elements are usually arranged in descending order. Under this convention, feature decomposition is unique if and only all eigenvalues are unique. Combined with fuzzy feature decomposition, the center distance of the scene reflected light intensity through the reflected light intensity of the image is shown in formula (3):

$$\Pi(\alpha, \beta) = \frac{\mu_{pq}}{(\mu_{00})^\gamma}, \quad (3)$$

where in μ_{pq} is the pixel transmission intensity of volleyball player's spike take-off image, μ_{00} is the initial pixel transmission intensity of volleyball player's spike take-off image, and γ is the histogram equalization parameter of the color space of volleyball player's spike take-off image. The method of histogram equalization control of color space is an important application of grayscale transformation, which is efficient and easy to implement. The grayscale of each pixel in the image is changed by changing the histogram of the image, which is mainly used to enhance the contrast of the image with a small dynamic range. If an image is generally dark or bright, then the method of histogram equalization is very suitable. The input image of the histogram equalization algorithm in OpenCV needs to be an eight-bit single-channel image, that is, a grayscale image. When calculating the equalization map of a color image, it is necessary to separate the channels of the image with the split function, process the images of each channel separately, and merge them with the merge function. The specific operation process is shown in Figure 2.

Based on the histogram equalization control method of color space, the enhanced discrete marker values are obtained. Using dark channel prior knowledge detection of guided filtering, the histogram of HSV color space is expressed as shown in formula (4):

$$J(x, y) = \begin{cases} \frac{\sum_{k=-s}^{+s} |\theta_m^{ij}(x+k, y+k) - \theta_n^{ij}(x+k, y+k)|}{(2s+1)^2}, & m \neq n \\ 0, & m = n \end{cases} \quad (4)$$

where in M and N are the action numbers of volleyball players' spike take-off action images, and I and J are the row and column numbers of marking points of volleyball players' spike take-off action images. s , k , θ_m^{ij} , θ_n^{ij} , respectively, represent the internal correlation feature quantity of volleyball players' spike and take-off action images. Combined with the analysis result of constraint parameters of the restored image, realizes the fusion of background values of the volleyball player's spike and take-off action image, and the output is shown in formula (5):

$$snq(C) = \max_{e \in MST(C,E)} w(e) + f(x_i + y_j), \quad (5)$$

where in $w(e)$ is pixel learning, $f(x_i + y_j)$ is the difference value between background image and action image. According to the difference between pixel value and background value, a feature dynamic recognition model of volleyball player's spike take-off action image is constructed, and the distribution sequence of character dynamic feature parameters of volleyball player's spike take-off action image is obtained as shown in formula (6):

$$\begin{aligned} c_1 &= \{i \mid i \in S\}, \\ c_2 &= \{\{i, i'\} \mid i' \in N_i, i \in S\}, \\ C &= c_1 \cup c_2. \end{aligned} \quad (6)$$

In the above formula, $i = 1, 2, \dots, T$ and $\{i, i'\}$ represent the highlight information of volleyball player's spike take-off action image. According to the background value and detail wavelet feature decomposition of volleyball player's spike take-off action image and the recognition result of DWT algorithm, edge contour feature detection processing is carried out to improve the ability to express the detail features of the image. The structure flow of enhancing recognition of volleyball player's spike take-off action image is shown in Figure 3.

Because the binary image data is simple enough, we can better analyze the outline of volleyball players' spike and take-off action images through binary images. There are many ways to binarize, among which the threshold method is the most commonly used [17, 18]. According to different ways of threshold selection, it can be divided into global threshold and local threshold. Global threshold is to select the same threshold value for every pixel in the whole image, which is realized by calculating the peak gray value in the image and then subtracting a set value. Pixel 0 is black and 255 is white. For each pixel value of the scanned image, if the

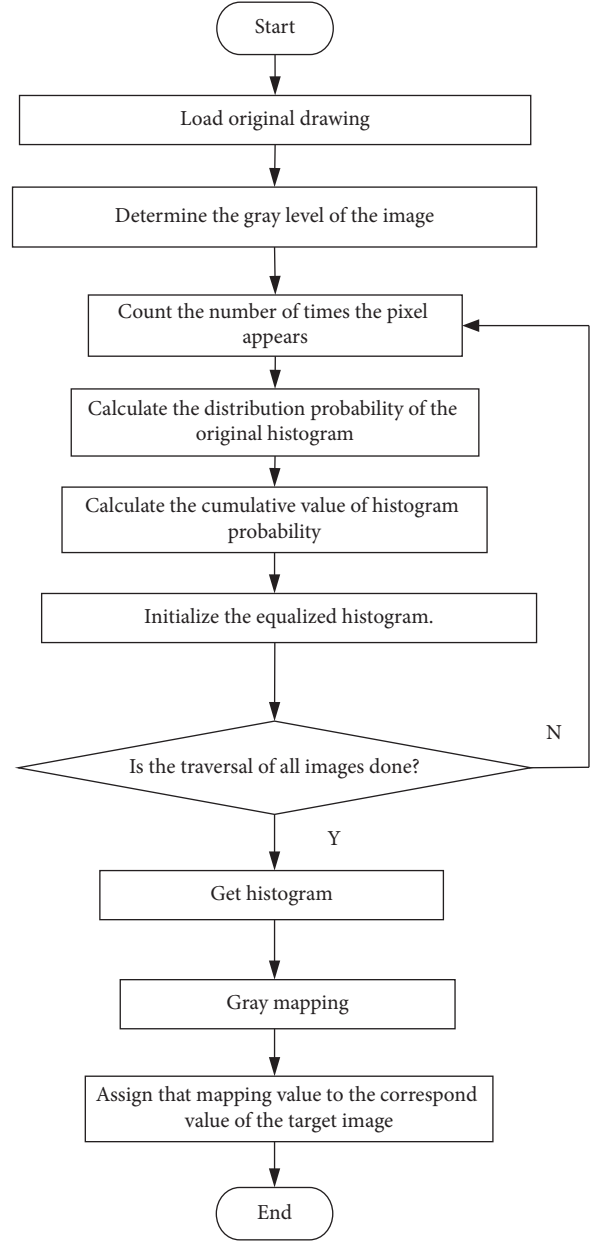


FIGURE 2: Operation process of histogram equalization.

pixel value is greater than the average value, the pixel value is set to 255, and the average value is set to 0 if the pixel value is less than or equal to 0. Local threshold is to take a small piece of an irregular image for threshold processing, and obtain it through mean filtering. The threshold value of each pixel is 1 when it is larger than this value, and 0 when it is smaller than this value. Set the gray value of the pixels on the volleyball player's spike take-off action image to 0 or 255. The whole image shows obvious black-and-white effect, and the discrete binarization of the image is completed. Short-time Fourier transform is used to determine the frequency and phase of local sine wave of time-varying signal, and a time-frequency localized window function is selected. Once the window function is determined, its shape will not change, and the resolution of short-time Fourier transform will be

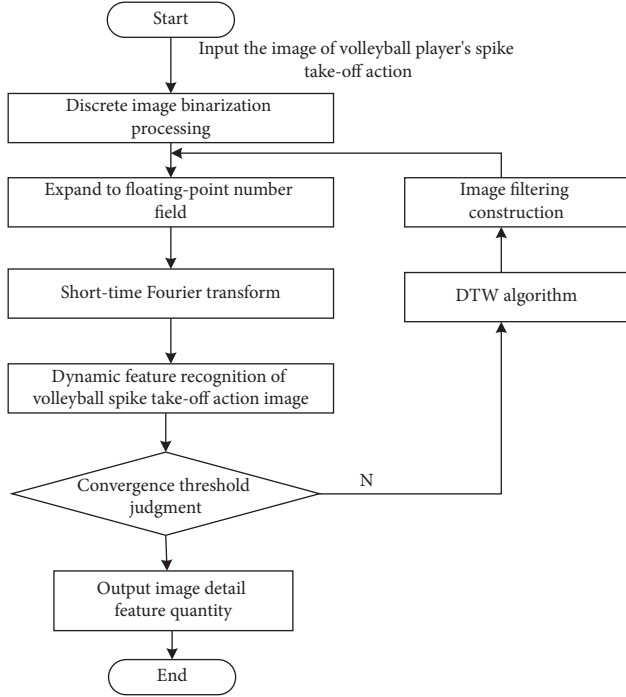


FIGURE 3: Structure flow of image enhancement recognition of volleyball players' spike take-off action.

fixed [19, 20]. If you want to change the resolution, you need to reselect the window function. After the short-time Fourier transform is completed, the dynamic characteristics of volleyball players' spike take-off action images are identified, and the convergence threshold is judged. If the convergence threshold is met, the detailed feature quantity of the spike take-off action image of volleyball players can be output, which provides support for the subsequent spike take-off action feature recognition of volleyball players.

3. Identification of the Characteristics of Volleyball Players' Spike and Take-Off Movements

On the basis of designing the visual data acquisition system of volleyball players' spike and take-off movements, it is necessary to design an algorithm for extracting the feature points of volleyball players' spike and take-off movements, and combine the coding transformation, quantification, and change of the lengthy coding of the predicted difference to improve the compression rate of the data stream to realize feature analysis, judge the error points of spike movements, realize the feature recognition, and construct a feature partition model for extracting feature points of the edge contour of the body. In the process of volleyball, combined with the positive movement intensity distribution of the edge contour characteristic unit under the human dynamics model [21], when the elbow of the player holding the ball gradually straightens and approaches downward, the ball rotates in the air, and the probability density function of the position distribution in the air after the ball is released is shown in formula (7):

$$P(I) = \omega v_{id}(t) + c_1 r_1 (p_{id} - x_{id}(t)) + c_2 r_2 (p_{pg} - x_{id}(t)), \quad (7)$$

where e represents the predicted value between frames. If the pixel I is a fixed code between frames, the compensation value relative to it can be regarded as zero, and e_n is the pixel value of the pixel i . The above-mentioned process can be reconstructed by quantization and inverse quantization in the encoder. Finally, through the edge contour viewpoint analysis, the communication coding error correction of visual information feature transmission is realized, and the feature collection of volleyball players' spike and take-off movements is carried out. With this technology, the multi-contour 3D model scene of volleyball players' spike and take-off movements is shown in formula (8).

$$\begin{aligned} \frac{\partial u(x, y; t)}{\partial t} &= \frac{\sigma}{\rho s} \nabla G(x, y; t), \\ &= k \left[\frac{\partial G_x(x, y; t)}{\partial x} + \frac{\partial G_y(x, y; t)}{\partial y} \right], \end{aligned} \quad (8)$$

where in, σ is the physical parameter of volleyball players' spike take-off, s is the position offset, ρ is the gray value of volleyball players' spike take-off image, $G(x, y; t)$ is the edge feature of volleyball players' spike take-off image, and SD represents the gradient. In the spike take-off, when throwing the ball and swinging the ball, the trend is perpendicular to the ground, and the technical feature of throwing the ball at 360 degrees is obtained. Standard normal distribution is a kind of normal distribution, and its average and standard deviation are fixed, with the average being 0 and the standard deviation being 1. Standard normal distribution is a kind of probability distribution of continuous random variables, which produces different distribution patterns according to the difference of the mean, standard deviation, and unit of random variables. The frequency proportion in any range can be estimated by calculating the mean and standard deviation of variables that obey normal distribution [22]. Furthermore, the standard normal distribution function is used to calculate the fluctuation of technical features in the spike take-off of volleyball players, shown in formula (9).

$$pk = \langle x_0, (x_i)_{0 \leq i \leq l-1}, (x'_i)_{0 \leq i \leq l-1}, (\Pi_i)_{0 \leq i \leq l-1} \rangle, \quad (9)$$

where in x_0 represents the initial configuration of volleyball player's spike take-off action, x_i is the characteristic distribution point, x'_i is the position rotation information of volleyball player's spike take-off action image, and Π_i is the continuous motion frame point. Sensors are used to automatically collect information of volleyball player's body position, volleyball angular velocity and rotation angle, etc. Assuming that the position conversion set relative to the root coordinate in the motion coordinate system, the target configuration of volleyball player's spike take-off is unknown, and assume that the shape error of the action amplitude of the spiking and receiving logic control unit at time t is $E[MB] = 1$, as shown in formula (10):

$$\eta = \frac{a}{a+b+c} \cdot \frac{E[MA] + E[MB]}{E[VA] + E[VB]}, \quad (10)$$

where in a , b , c , respectively, represent the edge contour parameters under the human dynamics model, VA , VB are the three-dimensional human body movement shape parameters of volleyball players' spike and take-off, MA , MB are the human body posture parameters of the local layer optimized to generate a new human body posture sample of the global layer, and the measurement equation of the spike area is shown in formula (11):

$$E[MA] = E[VA] = \sum_{i=0}^{\infty} i(1-p)^i p = \frac{1-p}{p}, \quad (11)$$

where i is the scalar feature point and p is the sample parameter of the candidate posture, the world coordinate system A and B are constructed, and the optimal candidate posture of each part of the human body is selected. The characteristic solution of the optimal action state is shown in formula (12):

$$\begin{aligned} \text{imag_err} &= T_{ij} - W_{ij}, \\ &= [\text{quater}(R)] \times [\text{quater}(Q_i) \times W'_{ij} + T_i] - W_{ij}, \\ &= \begin{bmatrix} u_{1j} - u'_{1j} \\ v_{1j} - v'_{1j} \\ \dots \\ u_{Fj} - u'_{Fj} \\ v_{Fj} - v'_{Fj} \end{bmatrix}, \end{aligned} \quad (12)$$

where in T_{ij} is the typed parameter of human body posture decomposing from global human body posture to local human body, W_{ij} is the space invariant moment of volleyball players' spike and take-off process, $\text{quater}(R)$ is the time invariant parameter, and $\text{quater}(Q_i)$ is the prior information of the video content of volleyball players' spike and take-off action. $u_{1j} - u'_{1j}$, $v_{1j} - v'_{1j}$, $u_{Fj} - u'_{Fj}$, respectively, represents the pixel distribution set of volleyball players' spike and take-off action images. In order to measure the similarity between Q_0 and Q_i , when a volleyball spike takes off, the racquet face is biased to the inner angle position and speed are \mathbf{p}_e , $\dot{\mathbf{p}}_e \in \mathbf{R}^{6 \times 1}$, respectively. The mass of the upper limb is decomposed into two acting forces, namely θ , $\theta \in \mathbf{R}^{10 \times 1}$, and the ball naturally lands on the thumb of the ball holder. Then, according to the end effect, inverse kinematics decomposition is carried out, and the differential equations of the spike under visual characteristics are obtained formula (13):

$$\dot{\mathbf{p}}_e = \mathbf{J}(\theta)\dot{\theta}, \quad (13)$$

where in $\mathbf{J}(\theta) \in \mathbf{R}^{6 \times 10}$ is the Jacobian matrix of volleyball players' spike and take-off movements. Jacobian matrix is similar to the derivative of multivariate function. In

vector calculus, the Jacobian matrix is a matrix in which the first partial derivatives are arranged in a certain way, and its determinant is called the Jacobian determinant. The importance of the Jacobian matrix is that it embodies a differentiable equation and the optimal linear approximation of the given points. In vector analysis, the Jacobian matrix is a matrix in which the first partial derivatives of functions are arranged in a certain way, and its determinant is called Jacobian determinant. In algebraic geometry, the Jacobian determinant of an algebraic curve represents a Jacobian cluster, which is accompanied by an algebraic group of the curve, into which the curve can be embedded. Jacobian matrix can reflect a differentiable equation and the optimal linear approximation of a given point [23]. According to the relationship between the distance of the center of mass and the coordinate axis, the kinematics solution of the direction, landing point, and rotation after the ball is released is shown in formula (14):

$$\dot{\theta} = \mathbf{J}^+ \dot{\mathbf{p}}_e + (\mathbf{I} - \mathbf{J}^+) \dot{\xi}, \quad (14)$$

where in $\mathbf{J}^+(\theta) = \mathbf{J}^T(\mathbf{J}\mathbf{J}^T)^{-1}$ is Moore-Penrose generalized inverse matrix \mathbf{J} of the matrix under the change of spiking position. Based on the above analysis, the physical characteristics of volleyball spiking are analyzed.

4. Detail Enhancement Processing of Image Action Feature Points

Using the dark channel prior analysis method of guided filtering, the information enhancement processing of volleyball player's spike take-off action image is carried out, and $(\Omega, F, f(x), P)$ is set as the standardized parameter value in the detailed feature distribution domain space of volleyball player's spike take-off action image. Based on the histogram control of HSV color space [24], the output HSV color space parameter information is obtained as $S = \{1, 2, \dots, N\}$, which represents the color feature component of volleyball player's spike take-off action image. Combined with the method of over-enhancement defect compensation, the detailed feature detection function of volleyball player's spike take-off action image is shown in formula (15):

$$\begin{aligned} C(i) &= \sum_{j=0}^i p_i(j), \\ &= \sum_{j=0}^i \frac{n_j}{n}, i \in 0, \dots, L-1, \end{aligned} \quad (15)$$

where in $p_i(j)$ is the weight factor, n_i is the limiting parameter, and n is the color feature of the outline. By using the dark channel prior distribution detection, the correlation feature quantity of the detail fuzzy parameter of the volleyball player's spike take-off action image in the range of $G_{\min} \sim G_{\max}$ is shown in formula (16):

$$g = G_{\min} + (G_{\min} - G_{\max})C(G), \quad (16)$$

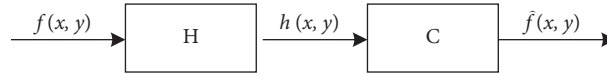


FIGURE 4: Image detail action feature point detail enhancement output.

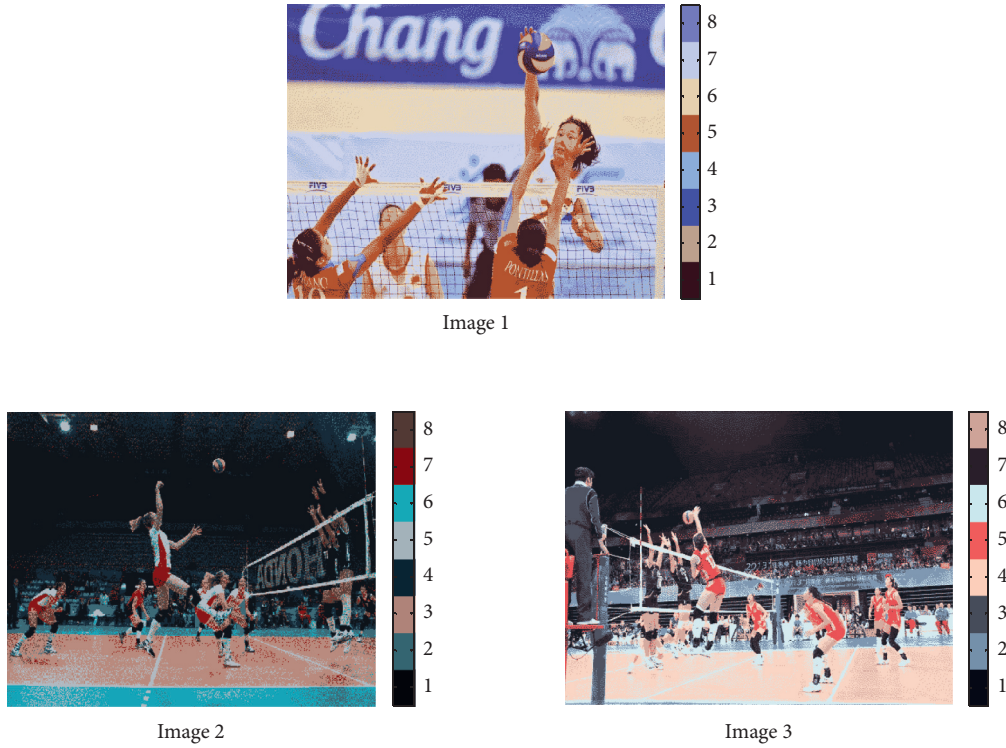


FIGURE 5: Test original drawing.

where in G_{\min} and G_{\max} represent the minimum and maximum statistical features, respectively, which are the interference components. By using the method of histogram equalization analysis, the dynamic block amount of the volleyball player's spike take-off action image is $C(G)$, and the contour details are enhanced in the sub-image blocks. The image guides the detailed image of the input volleyball player's spike and take-off action image to be filtered, and Sobel operator is used to detect the weak edge information of the animation image, and the detection threshold meets, is shown in formula (17):

$$|h(\vec{x})| - \delta \leq 0, \quad (17)$$

where in δ is the dark primary color component of the volleyball player's spike take-off action image. In summary, the details of the spike take-off action image of volleyball players are enhanced and the key action feature points are detected and amplified by using the methods of detail wavelet decomposition and DWT algorithm, and the high-order moment feature decomposition and wavelet feature separation in the edge area, so as to improve the ability of enhancing and identifying the details of the action feature points of the image [25]. The detail enhancement output of the image action feature points is shown in Figure 4.

5. Simulation and Test

In order to verify the application performance of this algorithm in the recognition of volleyball players' spike and take-off, OpenCV and Visual Studio are used for simulation experiments. In the recognition of human fine behavior in the video of volleyball players' spike and take-off, the spatial dimension in the image sequence can provide information of human environment, for example, what is the background in the environment, what tools are available, etc.; the temporal dimension can provide the movement information, for example, how volleyball players spike, how objects in the background and tools they operate move. At the same time, spatial image sequence and moving optical flow sequence are used to extract and process the information in the video. Four image sequences are used, and the recognition of volleyball players' spike and take-off action is guarantee to increase the extraction of the human operation area, which constitutes six image sequences. The sample data of volleyball spike take-off images come from Iris database, and the visual features are set as variables to analyze the performance of enhancing the details of volleyball spike take-off images. Three groups of volleyball spike take-off images are taken as test samples, and the original image is shown in Figure 5.



Image 1

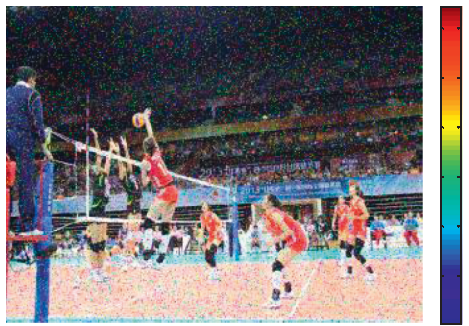


Image 2



Image 3

FIGURE 6: Image detail recognition results while $\sigma = 1$.



Image 1



Image 2



Image 3

FIGURE 7: Image detail recognition results while $\sigma = 2$.

TABLE 1: Test and comparison of performance parameters of spike take-off of volleyball players.

σ	PSNR (dB)			TR		
	This method	Harris	SUFR	This method	Harris	SUFR
1	26.41	14.34	13.75	28.33	20.41	10.29
2	28.35	14.54	13.80	28.29	22.57	10.29
3	28.71	14.55	13.84	28.49	22.57	10.32
4	28.95	14.68	13.87	28.84	22.97	10.33
5	29.11	14.69	13.87	28.84	22.97	10.35
6	29.14	14.75	13.92	29.46	23.67	10.36
7	29.43	14.84	13.93	29.80	24.05	10.36
8	29.76	15.01	13.97	29.87	24.13	10.38
9	30.05	15.15	14.02	30.63	24.95	10.44
10	30.20	15.17	14.04	31.25	25.65	10.46

Taking the volleyball player’s spike take-off action image shown in Figure 4 as the test sequence, this article captures the details of the volleyball player’s spike take-off action image, analyzes the contrast of the image by using the method of detail wavelet feature decomposition and DWT algorithm, and obtains that when the visual feature parameters $\sigma = 1$ and $\sigma = 2$ of the volleyball player spike take-off action are taken, the details enhancement and recognition results of the volleyball player spike take-off action image are shown in Figures 6 and 7.

Analysis of the simulation results in Figures 6 and 7 shows that with the increase of σ value, the brightness value of the shadow area of volleyball player’s spike take-off action increases greatly, and the pixel correction range of the blurred area of the three-dimensional image is large, but some details are lost. Taking the first group of images as an example, the PSNR and image entropy of volleyball player’s spike take-off action image are taken as TR test parameters, and when σ is 1~10, respectively, different methods are tested to enhance the details of volleyball player’s spike take-off action image. With the increase of σ value, the output PSNR of volleyball player’s spike and take-off action image becomes larger and larger. The average PSNR of this method is 37.7166 dB, which is 47.08% and 5808% higher than that of traditional Harris method and SUFR method. It shows that the output image of volleyball player’s spike and take-off action has better quality and higher entropy value, which shows that the contrast and clarity of details can be improved better Table 1.

Take Figure 8 as the original object to test the action recognition effect of this method, Harris method, and SUFR method. The results are shown in Figure 9.

It can be seen from Figure 9 that this method can identify all the details of volleyball players’ spike take-off action from the beginning to the end, which is consistent with the results in Figure 8. Harris method and SUFR method have different degrees of motion loss, which verifies the effectiveness of the proposed method.

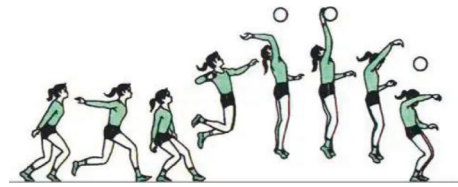
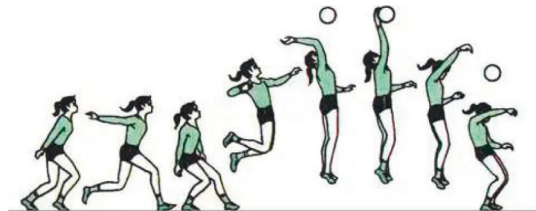
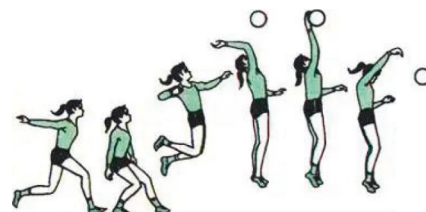


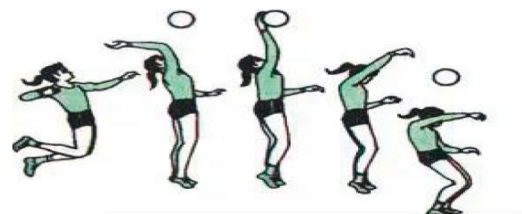
FIGURE 8: Original image sequence.



This method



Harris method



SUFR method

FIGURE 9: Image sequence test results.

According to the above analysis, DTW algorithm can accurately identify the spike take-off action of volleyball players, which has good image processing effect and good action recognition performance.

6. Conclusions

In this article, combined with the image recognition technology, the recognition technology of spike and take-off of volleyball players based on DTW algorithm is put forward, and the recognition model of spike and take-off of volleyball players is established, which can better analyze the action and technical characteristics of spike and take-off recognition items of volleyball players, and provide accurate data support for guiding spike and take-off training and competition referee of volleyball players. The transmission relation model of detail features of volleyball players' spike take-off action images is constructed, and the edge contour features of volleyball players' spike take-off action images are detected and processed by detail wavelet feature decomposition and DWT algorithm. Using prior Atlas knowledge instead of dark primary color, the detailed information and color of the image are obtained. Through the method of filtering and maintaining, the image is guided to filter the details of the input volleyball player's spike and take-off action image. Sobel operator is used to detect the weak edge information of the animation image. In the edge area, high-order moment feature decomposition and wavelet feature separation are used to enhance the details of the volleyball player's spike and take-off action image and detect and enlarge the key action feature points, so as to improve the ability of enhancing and identifying the details of the action feature points of the image. The test shows that this method can effectively solve the noise and error in the process of recognizing the spike and take-off action of volleyball players, reduce the recognition error, and improve the ability to accurately locate the spike and take-off force point. This method has a good application value in improving the training guidance of volleyball players' spike.

Data Availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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