

Retraction

Retracted: Modeling and Simulation of Tennis Serve Image Path Correction Optimization Based on Deep Learning

Wireless Communications and Mobile Computing

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

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WILEY WINDOw

Research Article

Modeling and Simulation of Tennis Serve Image Path Correction Optimization Based on Deep Learning

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The traditional tennis serve training model has been deeply ingrained in the current training. For athletes, in order to master the essentials of technical movements proficiently, they must practice for a long time and repeatedly according to the guidance of coaches. Effectively correcting the image path of tennis serve can improve the level of tennis training and competition. When correcting the image path of the tennis serve, it is necessary to mark the corners of the error points according to the characteristics of rotating multidimensional characteristics of the serving action. The traditional method adopts the critical node control method to realize the extraction of limb features and complete the path correction of the serving image. The error points of the process are marked, which reduces the accuracy of the path correction. Based on the deep learning model, this paper proposes an optimization modeling method for tennis serve image path correction and builds a visual feature acquisition system for tennis serve action based on remote video monitoring. The processing method designs the edge segmentation algorithm for the collected visual images and, on this basis, marks the corner points of the error points of the serving action and realizes the optimal modeling of the path correction of the tennis serving image. In this paper, the DLT algorithm and MSDLT algorithm are compared first, and then, the DLT algorithm is compared with the algorithm in this paper. The results show that the success rate of this method is about 92%, while the success rate of DLT algorithm is only about 82%. This algorithm has obvious advantages. The method in this paper is used to correct the action shape of the tennis serving action, which has better real time and accuracy and superior performance and can accurately track the visual edge information feature points of the player during the serving process.

1. Introduction

Vision is the most direct sense for human beings to experience the environment, and the main way for humans to understand external information is through vision. In the rapid development of computer vision and the rapid progress of informatization, scientific and modern training technology has been widely used in tennis [1]. Sports analysis based on deep learning plays an important role in sports fields such as competitive sports and skill sports, because it can obtain accurate and comprehensive information of sports personnel through camera devices without causing any interference to athletes. Sports data further analyze the technical movements of athletes, help coaches and athletes to find irregular movements or wrong movements, improve the efficiency of sports training, and improve sports techniques, so as to achieve the purpose of auxiliary training [2].

The analysis process of tennis serve image path analysis requires the establishment of a physical model of the human body including geometric parameters, human inertial parameters, and muscle force parameters, and a mathematical model for dynamic solution. The numerical-aided analysis of the method can provide some useful information, which can reduce the cost of research and save a lot of time, which is of great significance to the action guidance in physical education, the improvement of sports performance, and the prevention of sports injuries [3]. Tennis serve image path analysis technology is usually used in information engineering projects. The commonly used technology for tennis serve image path analysis is simulation technology. Sports scholars in my country do not have a clear understanding of computer simulation. It cannot be distinguished from the kinematic analysis system. The significance of simulation lies in its predictability, and it can be combined with relevant action technical analysis to show relevant diagnostics. Simulation should not only be formed by modeling and animation performance of actions but also should be more on how to make students, teachers, and sports researchers have a macrounderstanding of an action technique [4].

For athletes, in order to master the essentials of technical movements proficiently, they must practice for a long time and repeatedly according to the guidance of coaches. The use of experience-based training methods for a long time, relying on the subjective awareness of coaches to guide and supervise the technical movements of athletes, this situation seriously restricts the improvement of tennis level [5]. Various methods based on CNNs have been applied to multiple tasks in image processing and machine vision and achieved excellent performance, proving that CNNs have better features for image data than feedforward neural networks' learning ability. In addition, the offline prelearning process greatly limits the practicability of online object tracking systems. In view of this, this paper studies how to apply deep CNNs to the appearance modeling task in online object tracking systems based on small-sample sets. Although deep CNNs have achieved great success in various offline tasks with large images and large amounts of data, when they are directly applied to learning tasks on small online training data sets, the network is prone to overfitting. And it is more sensitive to low-reliability training samples [6]. The application of deep learning technology in tennis training is becoming more and more common. It not only breaks the traditional shackles of subjective judgments of athletes' technical movements by coaches only with naked eyes and experience but also allows athletes to perform training videos on their own analysis and found the deficiencies, which is conducive to improving the training efficiency more intuitively [7].

Section arrangement of this paper is as follows: Section 1 introduces the related research on the combination of tennis training and computer images by relevant scholars and puts forward a summary based on the above literature. Section 2 introduces related technologies of deep learning algorithms. Section 3 is based on deep learning models, modeling the frequency capture of tennis service path. Section 4 compares and analyzes the algorithm in this paper and DLT. Section 5 is the summary of the full text.

The innovation of this paper is as follows: For a tennis path tracking task, the performance of the tennis path model mainly depends on which feature description operator and which statistical modeling learning method is used. An online tennis path tracking method based on appearance modeling of deep CNN is proposed. The particle resampling method solves the problems of easy overfitting and sensitivity to noise samples when deep CNN is applied to small sample sets online. Aiming at the small tennis path tracking task that deep feature learning cannot handle, this paper proposes a hierarchical data association method based on the idea of hierarchical processing and successfully combines local and global trajectory constraint information through dynamic programming and graph theory methods to help filter out. A large number of fake tennis path trajectories are used to obtain the final robust tennis path trajectories.

2. Related Work

In the traditional tennis training method, the motion range detection method is used for the tennis serve action, and it is not applicable to the sports items such as the tennis serve action where the motion range presents the multidimensional characteristics of landing and rotation. The use of video image processing technology in tennis training has become more and more common. It not only breaks the traditional shackles that coaches make subjective judgments on players' technical movements based on naked eyes and experience but also allows players to use their own training videos. Analysis is carried out to find out the deficiencies, which is beneficial to improve the training efficiency more intuitively [8, 9].

We developed a visual sensor network VSN (visual sensor network). These autonomous, wireless communication VSN nodes are very small and battery powered, which makes them ideal for monitoring tennis daily training and matches in any situation, and tracking tennis players' movement information on the court in real time [10]. Wan and Shan studied the relationship between the relative movement of the middle and lower torso and lower body muscle activity during three different types of serve (flat serve, topspin serve, and cut serve), considering the way of joint torque generation in tennis serve, in order to explore the quantitative relationship between the joint torque of the upper body and the speed of the racket head [11]. In order to improve the teaching quality of tennis lessons, computer-aided teaching was introduced into the teaching of tennis. 120 students were selected to participate in the experiment, and the subjects were divided into two groups: the control group and the experimental group. The experimental results show that the use of computer-aided teaching methods to set up scenarios can inspire students' enthusiasm for learning tennis skills to a certain extent. The assessment results show that students are more active in learning the basic skills and knowledge of tennis; they are more likely to enter the best learning state. Through the integration of various teaching methods, students can be better taught in accordance with their aptitude to achieve teaching optimization [12]. Chen H takes 6 young tennis players and 2 young tennis players as the research objects through the three-dimensional high-speed camera and the linear change method, and the research objects have achieved good results in many competitions. Data analysis collected the kinematic parameters of their strong serve. The data show that the movement speed of each joint point of the athlete's body has obvious characteristics when serving the ball. The force is then transmitted to the trunk, upper limbs, acceleration and braking in turn, and finally to the racket. This shows that the tennis serve is a typical whipping action. Through whipping, the force of each joint of the body is transmitted to the racket, and finally, the racket obtains a huge hitting speed and power [13]. Fang et al. conducted a detailed study on the technical action of tennis high pressure ball by using 3D stereo photography analysis method and obtained the kinematic parameters of the action.

The analysis results show that when hitting the ground, the order of force is thigh, calf, and foot; in the process of hitting the ball from top to bottom, the movement speed of the three joints of shoulder, racket arm elbow, and wrist. basically the same; the angular velocity of the shoulder peaked first, and the peak angular velocity of the elbow and wrist appeared at the same time. The experimental results reveal the kinematic characteristics of tennis high pressure technology and provide scientific guidance for quantitative analysis of tennis training and teaching [14]. Hayes et al. pointed out that serving technology plays a large part in tennis technology and elaborated on how to improve the teaching and training of technology. Begin to guide students to learn tennis. Few teachers start teaching from serving, ignoring this important technical link, which leads to students' mastering of serving skills being not very ideal. Unsatisfactory or even backward, this is an important reason why it is difficult to achieve breakthrough improvement in serving technology [15]. Zenker and Klein pointed out that there are the following situations in the teaching of serving technique: the tossing is unstable, the tossing is the premise and foundation of good tennis serving quality, and the eyes fail to focus on the ball during the tossing process, which makes it impossible to judge the correct hitting point, which affects the entire serving action [16]. Wang et al. used the PTI 3D motion capture system to collect the kinematic data of tennis players of different sports levels. Two PTI trackers and one wireless marker receiver were used in the experiment. Referring to V3D stickers, we obtained the motion trajectories of different subjects during the serving process, the change of the center speed of each link, the change of the central momentum of each link, the comparison of the rotation angle of each link, and the lead, swing and follow-swing movements in the serving action process. In the time proportion of the process, through its analysis of the kinematic data, it is concluded that when the athlete takes a large proportion of the time, the more elastic potential energy can be accumulated, so that the end can obtain more kinetic energy [17]. Myers et al. used two KODAK highspeed cameras and the shooting frequency of 500 frames per second to film the serving skills of 26 key men and women of the national tennis team and found that reasonable serving skills are more. It is beneficial to use the muscles of the whole body when serving, and it is emphasized that athletes should pay attention to finding the rhythm of the serving action that suits them [18]. Zhu et al. divided the upper body and racket into 11 interconnected parts through mathematical modeling and specifically quantified the contribution of each part to the speed of the head of the racket [19].

Video-based human motion analysis is an important research direction in the field of computer vision. It detects moving objects from video sequences, extracts key parts of the human body, obtains useful information about human motion, and realizes further analysis of human motion, posture, etc. and identification. The traditional tennis serve training model has been deeply ingrained in the current training. The application of deep learning technology in tennis training is becoming more and more common. It not only breaks the traditional shackles of subjective judgments of athletes' technical movements by coaches only by naked eyes and experience but also allows athletes to perform training videos on their own. Analyze and find out the deficiencies, which is conducive to improving the training efficiency more intuitively.

3. Theoretical Techniques Related to Deep Learning

3.1. CNN. CNN is another special neural network model. Different from the abovementioned feedforward neural network, the CNN is usually composed of three types of hidden layers which are connected in series. The sparse local connection between adjacent layers can better mine the spatial local features in the image, as shown in Figure 1.

A CNN is basically composed of a plurality of convolution layers connected in sequence, and each convolution layer is provided with a plurality of convolution kernels [20]. The convolution kernels in each convolution layer scan the whole processed image in sequence from left to right and from top to bottom, and the data of the feature map obtained is output [21]. The weight sharing mechanism greatly reduces the number of training parameters in the model, and the learned visual features are not sensitive to the absolute position in the field of view, so that the image feature extraction is more effective [22, 23]. The above characteristics make CNNs have better learning and generalization capabilities than ordinary feedforward neural networks for visual tasks. The process of obtaining the feature map output by the weight layer through the convolution operation is expressed as

$$\mathbf{x}_{ij} = f\left(\sum_{i \in F} {x_{ik}^{j}}^* \boldsymbol{b}_{ij} + k_j^i\right). \tag{1}$$

The usual pooling operation is to downsample the nonoverlapping regions of the input feature map, so the size of the output feature map is a fraction of the size of the input feature map. There are two main types of weight layer in common use today: max pooling and mean pooling. The general form of the weight layer is also equipped with an additive bias factor and a multiplicative bias factor, so most of the current weight layer of CNNs omit these parameters, that is, the weight layer is generally not. The main difference between the two pooling operations is that the final pooled output value is the maximum value or the average value of each corresponding small area. The general form of weight layer operations in CNNs can be expressed as shown in

$$x_{ij} = f\left(\beta_i^j \text{pooling}\left(x_j^{x-1}\right) + k_i^j\right),\tag{2}$$

$$\frac{\partial k_{ij}}{\partial E} = \sum_{u,v} \left(\delta_j\right)_{uv}.$$
(3)

Each feature map of the weight layer has its own error sensitivity, and its value is the sum of the contributions of all convolution kernels in the weight layer, as shown in

$$\delta_{j} = \sum_{i=1}^{i} \delta_{j+1}^{i} + b_{j+1}^{i}.$$
 (4)



FIGURE 1: Schematic diagram of CNN structure.

The parameter to be trained in the weight layer is the convolution kernel, which is multiplied point by point with the convolution kernel to generate the feature value of the feature map.

3.2. BPNN Model. The basic idea of the BPNN is that in the learning process, it is composed of two processes, the forward propagation of the signal and the back propagation of the error. During forward propagation, the input samples are passed in from the input layer, and after each hidden layer is processed layer by layer, they are transmitted to the output layer. If the actual output of the output layer does not match the expected output, it is transferred to the backpropagation stage of the error. The error backpropagation transfers the output error layer by layer from the hidden layer to the input layer in a certain form and inverts the output error to all units of each layer, so as to obtain the error signal of each layer unit, which is the correction. The basis for the weight of each unit. The structure of the BP weight layer neural network is shown in Figure 2.

In the symmetric form of jump distribution, then the calculation of acceptance rate can be expressed as shown in

$$\alpha = \frac{p(x^t)}{p(x^{t-1})}.$$
(5)

In practical applications, it is often necessary to carefully monitor the size of the acceptance rate in each round. If the acceptance rate is too high, it means that the sampling chain cannot move fast enough in the sample space; if the acceptance rate is too low, it means that the sampler rejects too many samples, resulting in inefficiency. For fast-moving targets, even in consecutive frames, the position of its motion varies greatly, and the frame difference method based on two frames cannot achieve the purpose of detection. The frame difference method based on three frames of images can realize the detection of this situation as shown in

$$D_{n+1} = |k_{n+1}x(x,y) - k(x,y)|,$$
(6)

$$D_n = |k_n x(x, y) - k_{n-1}(x, y)|.$$
(7)

In the process of using the frame difference method to detect the target, the frame difference method has a good effect on the detection of moving objects, and the detection speed is fast, but its frame difference method also has many shortcomings. For a typical online object tracking task, the initial position of the tracked object is usually annotated in the form of a rectangular bounding box in the first frame of the image sequence. When using the BPNN to model the appearance of the target, it is necessary to extract positive and negative samples according to the annotation in the first frame, so that the network can be initialized and trained to converge. Therefore, the BPNN will take a little time to initialize the first frame to obtain better initial model parameters. In the online tracking process, the method in this paper uses a lazy update strategy for the BPNN model, that is, only when the confidence of the predicted target is less than an empirical threshold, the network parameters will be fine-tuned and updated; otherwise, the network model parameters will not be updated.

4. Modeling of Tennis Serve Trajectory Tracking Based on Deep Learning

4.1. Image Indicators of Tennis Serve Path. In order to detect possible tennis targets, we filter out all possible target candidates from the difference map of adjacent image frames by color and size information. Due to the small size of the tracking target, cluttered background, occlusion, and noise, multiple candidate targets are detected in each image frame. In addition, in practice, there are many false candidate targets due to the movement of the camera and the movement of the players. Therefore, this paper detects the field lines of the court and tracks the players to help filter out these false target candidates as much as possible.

The existence of noise greatly interferes with the image information, which will adversely affect the subsequent analysis of the image. In order to suppress noise, image denoising must be performed to improve image quality [20]. In the process of acquisition, conversion, and transmission of images in reality, they are often interfered by the factors of the imaging equipment itself and external conditions, resulting in some random, discrete, or isolated points on the image [24]. While filtering out noise, the edge information of the image can be well preserved. In order to be more representative, this paper chooses to intercept 20 frames of pictures in a serving motion to train a dictionary of serving actions, and then, the dictionary can be applied to the entire video stream through sparse representation reconstruction denoising. This paper uses three common objective evaluation criteria for comparison, namely, MSE, PSNR, and FSIM. The comparison of the three denoising methods using different evaluation indicators is shown in Table 1.



FIGURE 2: BPNN structure.

TABLE 1: Comparison of different denoising indicators.

Algorithm	PSNR	MSE	FSIM	Running time (s)
Median filter	33.1832	39.4841	0.9218	8.28
Wavelet denoising	38.2103	26.6242	0.9783	11.41
Sparse denoising	36.3937	18.2452	0.9975	215.24

Based on the field of moving target detection and tracking, there are two sliding window strategies in the prediction stage: one is to use sliding windows of different sizes, extract features for each sliding window, classify and determine whether it is the target, and finally use the algorithm to select an effective detection as a result; another strategy is to construct an image pyramid, only use a sliding window of one size to slide on all pyramid images, extract features for each sliding window and classify it to determine whether it is the target, and finally use an algorithm to select effective detection results. The main principle is to obtain the target area moving in the continuous frames by processing the continuous frames in the video. The acquisition of consecutive frames generally selects two or three frames of images within the same time interval. The processing method is to obtain the difference image by subtracting the corresponding images of the images. After the difference image is obtained, the background and moving images are obtained by threshold segmentation. The comparisons of various aspects of the interframe difference method, the background subtraction method, and the optical flow method are shown in Table 2.

With the continuous addition of new prediction data points in the test set, the performance of the prediction model will gradually decline, and the error between the prediction results and the real results will become larger and larger. This section qualitatively analyzes the tracking method in this paper in terms of light change, occlusion, deformation, and rotation and compares it with other algorithms. The comparison results are shown in Figures 3 and 4.

The changes of ambient light are common in real scenes and have different degrees of influence on the extraction of image features. The tracking method proposed in this paper incorporates hierarchical features learned by deep neural networks. It is not difficult to see from the tracking results that different degrees of drift have appeared in the first light change, but they are obviously not well adapted to the scale changes of the target car. The tracking method in this paper has no drift problem in the two obvious changes of light, and at the same, time has a good adaptability to the stable scale change of the tracking target. This also benefits from the local normalization that the network does when inputting images. In order to better adapt to the obvious scale changes of the tracking target, in the particle filter, the variance of the particle evolution needs to be enlarged accordingly; at the same time, in order to prevent the particles from being too sparse, the number of particles also needs to be increased accordingly.

The efficiency and accuracy of traditional target detection gradually lag behind people's needs. Traditional object detection methods are mostly based on artificially designed feature accuracy, resulting in poor robustness. With the breakthrough of computer performance bottleneck, deep learning technology has developed rapidly. In the deep learning stage of target detection, CNN is used for feature extraction. Computer hardware is also constantly developing. The advancement of GPU has greatly improved the computing performance of computers. The above factors have accelerated the development of target detection.

4.2. Tennis Track Line Detection. In order to predict the position of the ball in the first specific frame, a local physical motion model can be estimated according to the positions of the candidate targets in the first three frames. Here, the prediction results in different frames obtained according to the physical motion model are recorded as time. As a result, and simplifying the process, this paper assumes a constant acceleration of the tennis ball during flight. For any adjacent triplet in the middle of such a path in a static scene, the background model can be photographed in advance without foreground moving objects or noise. The difference processing is performed between the current image frame and the background reference model, the moving target area is determined by the change of the information in the statistical histogram, or the gray feature change is determined, and finally, the difference result image is subjected to threshold determination

Method name	Difference between frames	Background subtraction	Optical flow method
Scope of application	Fixed camera	Fixed camera	Fixed and nonfixed cameras
Detection principle	Image difference between two or three consecutive frames	Difference between current frame and background model	Optical flow characteristics over time
Detection effect	Incomplete foreground area	More complete foreground area	More complete foreground area
The complexity	Simple	Generally	Complex
Robustness	Susceptible to environmental influences	Strong adaptability to the environment	Susceptible to environmental influences
Real-time	Good	Good	Difference

TABLE 2: Comparison of different target detection algorithms.



FIGURE 3: The accuracy curve of the tracking algorithm under different VOR thresholds.



FIGURE 4: The correct rate curve of the tracking algorithm under different CLE thresholds.



FIGURE 6: Coverage curve.

calculation. In order to show the tracking effect more intuitively, this paper takes DLT and MSDLT as examples to show their center point error curves and coverage curves, as shown in Figures 5 and 6.

The high frequency of occlusion in video sequences occurs because when the target is severely occluded, the number of matched feature points decreases, and the neural network needs to be updated. If the number of frames is too large or the occlusion part is too large, the tracking will fail. Tennis motion trajectory tracking and detection based on deep learning uses the noise reduction autoencoder to learn the highlevel abstract features of the target, combined with the features with scale invariance, which improves the accuracy of target tracking in complex motion scenes, and further strengthens the proposed algorithm. Robustness of scale-variant tennis trajectory tracking was obtained.

5. Output of Tennis Serve Image Path Correction Results Based on Deep Learning

When the method in this paper is used to correct and optimize the path of the tennis serve image, the image processing method is used to segment the edge of the collected visual image, and based on this, the corner points of the error points of the serve action are marked to realize the path correction and optimization of the tennis serve image. The output results are compared with DLT, and the comparison results are shown in Figure 7.

It can be seen from Figure 7 that the success rate of this method is about 92%, while the success rate of DLT and MSDLT algorithms is only about 82%. This algorithm has obvious advantages. The method in this paper is used to correct the action shape of the tennis serving action. It has better real time and accuracy and superior performance. It can accurately track



FIGURE 7: Algorithm comparison.

the visual edge information feature points of the player during the serving process and conduct real-time evaluation and guidance through the expert system. Correcting the incorrect, it can improve the serving skills and mark the corner points of the error points of the serving action, so as to realize the optimization and modeling of the tennis serving image path correction.

6. Conclusions

In this paper, an optimization modeling method of tennis serve image path correction based on deep learning model extraction is proposed. Experiments show that the success rate of this method is about 92%, while the success rate of DLT and MSDLT algorithms is only about 82%. This algorithm has good real time and accuracy and superior performance and can accurately track the visual edge information feature points of players in the process of serving. It can effectively correct the image path of tennis serving and improve the serving skills through real-time evaluation and guidance by an expert system.

Because the target detection needs to process the difference between the image to be detected in each video frame and the background image model, the modeling method of the background model is very important for the accuracy of this method, and the accuracy of its model directly affects the target motion detection result. In the follow-up study, we will establish a human body model to study the angle and angular velocity of each joint in the process of serving and the correlation between each joint point and the ball speed.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no competing interest.

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