Scholar Publishing Group
International Journal of Sports Technology
https://doi.org/10.38007/IJST.2022.030304
ISSN 2789-7141 Vol. 3, Issue 3: 53-65

Adaptive Monitoring Technology of Basketball Video Image under Intelligent Network

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Keywords: Basketball Video Image, Intelligent Network, Adaptive Monitoring, Image Processing

Abstract: At present, sports have become a frequent international competitive exchange activity. To a certain extent, a country's sports level also measures the country's comprehensive economic strength. In recent years, computer technology has injected new vitality into most industries, but its development in sports has been relatively slow. This paper mainly studies the basketball video image adaptive monitoring technology under the intelligent network. In this paper, the semantic information of events in basketball videos is extracted by extracting a type of characters and image information added by the video editor in the video screens in basketball videos, namely basketball video event monitoring. There is a direct correspondence between the non-scene target information in the basketball video and the semantics of the game event. Using this relationship, a low-complexity and effective adaptive monitoring method for basketball video images can be designed. Firstly, the basketball video is divided into two parts: video image data and video and audio data. The audio data part is analyzed to extract relevant audio features. Then the video image data part is divided according to the structure and divided into video frame images. There are three layers of shots and video events/scenes. Related image features are extracted for the video image layer, and middle-level semantic features are defined for the video shots. The algorithm uses the change characteristics of pixels in the time dimension that are more effective than traditional image area features to locate and recognize non-scene targets in the video, and then use the direct correspondence between non-scene target information and basketball video events to perform event. The experimental results show that the accuracy of the method in the experiment is 98.31%, and the recall rate is 99.09%. The algorithm proposed in this paper can obtain a higher accuracy rate of basketball video event monitoring than traditional algorithms.

1. Introduction

In recent years, with the popularization of video capture devices and the continuous improvement of computer performance, a large number of videos are stored in digital form. Effective use of this resource will provide a lot of valuable information for various industries and fields. After long-term practice and research, domestic and foreign sports experts agree that the introduction of digital video technology into sports training can greatly improve training efficiency.

The basketball coach is the main body who imparts advanced and specialized skills of basketball to the players, and is the designer and organizer of scientific training [1]. The process of basketball movement, training, and competition should be completed under the guidance of advanced tactics. Especially in the process of confrontation, the coach's ability to analyze and recognize the opponent's tactics is directly related to the use of the tactics of the players of the team, which in turn determines the performance of the game. The current manual monitoring method is no longer able to meet the demand of basketball video image monitoring. Affected by external interference, the monitoring effect of basketball video image at low bit rate is poor, and the monitoring cost will increase substantially [2]. Therefore, an efficient and accurate monitoring method is needed to replace the current monitoring mode.

In mobile ad hoc networks (MAC), the existing MAC protocol based on short-time busy notification is not an effective data segmentation method. In addition, adjusting the length of data fragments according to the network environment is still a problem. Inamdar uses ant colony optimization (ACO) technology to design an adaptive directivity monitoring MAC (ADM-MAC) protocol for smart antennas. In this technology, he uses ant colony optimization (ACO) technology to estimate network density and traffic intensity information, and then passes it to the MAC protocol. Then, data segment transmission is performed by adaptively adjusting the direction monitoring period based on the packet size. His method has poor error tolerance and poor adaptation [3]. Ueyama discussed two research questions arising from the adaptive ubicomp system: What are the key requirements for providing a reliable WSN-based system? How to develop an adaptable and reliable WSN-based system? He used the RESS standard platform to answer the previous question. The latter question is answered by adopting a general adaptation method. Their RESS standard verification experiment failed and the standard was invalid [4]. Context adaptive monitoring is a method used in various domains to respond to changing conditions. Zavala carried out systematic mapping research on adaptive monitoring methods. They have applied automatic search and snowball sampling from different sources, and used strict selection criteria to retrieve the final essay collection. In addition, they used existing qualitative analysis methods to extract relevant data from the research. Finally, they applied data mining techniques to identify patterns in the solution. Their method is not efficient in monitoring and cannot meet the application requirements [5].

This paper proposes an adaptive monitoring method for basketball video images under the intelligent network. A hierarchical structure composed of auxiliary features and main features is defined in advance, and the layers are related through the suggested distribution of particles. During player monitoring, according to the correlation between levels, the main feature particles are guided by auxiliary features to move to the area close to the target to optimize the update of the main feature particle proposal distribution, so that the particle proposal distribution is closer to the true posterior probability distribution of the target. This method only needs a small number of high-confidence particles to represent the posterior probability distribution of the target, which reduces the amount of system calculation and improves the real-time tracking. At the same time, because the local feature and a local feature self-update strategy are used in the tracking process, when the target is deformed, partially occluded and the local feature disappears or the local feature "drifts" into the background, the local feature will be replaced by the new local feature Replaced, thereby enhancing the anti-blocking ability of monitoring.

2. Basketball Video Image Adaptive Monitoring Method

2.1. Dynamic Bayesian Network

A dynamic Bayesian network is an expansion of a Bayesian network with the same structure on the time axis. In essence, a dynamic Bayesian network is still a Bayesian network, but its periodic structure is more suitable for processing time signals. The dynamic Bayesian network can be expressed as T-frame time slices Z along the time axis [6], each frame has N nodes Z, DBN meets the following two conditions: the node of the current frame depends on the node or frame of the previous frame Other nodes inside (first-order Markov model), but have no relationship with the nodes before the previous frame; the dependency relationship is one-way [7]. Dependency satisfies time invariance. Based on the above assumptions, the probability of the joint distribution of DBN is expressed as

$$P\left(Z_{1:T}^{1:N}\right)=\prod_{l=1}^{N} P_{B_1}\left(Z_t^{(i)} \middle| Pa\left(Z_t^{(i)}\right)\right)\times\prod_{t=2}^{T}\prod_{t=1}^{N} P_{B\to}\left(Z_t^{(i)} \middle| Pa\left(Z_t^{(i)}\right)\right) \tag{1}$$

In the formula (1), T is the total number of frames, the first formula on the right is the start probability of the frame, and the second formula is the transition probability between frames.

Dynamic Bayesian networks are usually used to represent time-related system events. The nodes in DBN can be divided into two parts: the lower nodes represent the external observations of the system [8], which are generally measurable values; the upper nodes represent the system’s the internal state is generally hidden. Commonly used to model time systems are Kalman Filter Model (KFM) and Hidden Markov Model (HMM), both of which can be regarded as special cases of DBN [9]. KFM is usually used to represent a DBN with continuous observation nodes and state nodes, and HMM is usually a DBN that represents discrete state nodes.

Compared with traditional HMM, DBN has more powerful statistical modeling capabilities. In HMM, there is only one hidden state node and one observation node in each time frame. DBN allows multiple nodes. Although this will increase the amount of calculation, it also gives DBN more flexibility [10]. For example, a time frame can use multiple observation nodes corresponding to different characteristic values, similarly, multiple variables can be used to represent the internal state of the system [11].

Generally, the nodes in the DBN can directly correspond to the real system, and the conditional probability can be set by experts, or it can be learned from training data. In HMM, the physical concepts in the actual system can generally be corresponded to hidden state variables, such as whistles in the sound. However, this correspondence is limited, especially for multi-level semantic concepts in sports videos, it is difficult to fully express with only one state variable [12]. With DBN, we can describe semantic events and their relationships in video content well based on domain knowledge.

In addition, in DBN, nodes are not completely connected. In fact, some nodes are conditionally independent. Conditional independence helps reduce the amount of calculation of joint probability, which is another advantage of using DBN. A dynamic Bayes model is transformed into a hidden

Markov model, they have the same state space [13]. The DBN has two state nodes A and B. A has 3 states and B has 4 states. The number of system states that can be expressed is $3\times4=12$. C and D are observation nodes, both of which are 3-dimensional feature vectors. When the hidden Markov model is used to describe the system, the state number of the state variable is 12, and the observation vector of the HMM is 6-dimensional. Compared with DBN, the joint probability of the same HMM requires more data and parameters to represent and calculate [14].

The learning and reasoning algorithm of DBN is similar to that of Bayesian network. Here, we make a comparison between DBN and H MM. In HMM, there are three basic problems, decoding (Decoding) problem, evaluation (Evaluation) problem and learning (Learning) problem. The decoding problem is to solve the internal state of the system under the condition of a given observation sequence; the evaluation problem is to calculate the probability of the observation sequence [15]. Both of these problems are probabilistic inference problems under Bayesian networks, and the calculation methods include Junction Tree algorithm and its variants. Parameter learning problems can be solved by Bayesian network learning algorithms, such as EM algorithms.

2.2. Movement Target Calibration

For complex situations such as on a basketball court, because the foreground moving target occupies a larger space relative to the field of view, it is easier for players to be occluded if they are close to each other. If the foreground is detected by the background difference method, there are problems such as adhesion. The image processing algorithm based on player number recognition cannot recognize the target if the player’s back to the camera when recognizing a moving target. Therefore, for the particularity of the basketball game, none of the above methods can effectively recognize the situation of multiple sports targets, so it is difficult to calibrate a single target. The position of the sports target, and the background of the basketball court is more complex [16], the stands are close to the court, the audience is likely to affect the static background in the video and appear as the foreground. Many methods based on the background difference method or the method cannot effectively obtain the player target, so that the tracking effect is not ideal [17].

Use adaptive Gaussian mixture model for background modeling and target detection. First determine the approximate distribution of the main colors of the stadium, and then use the Gaussian mixture model to fit it. The middle circle and the three-second area can be identified and excluded because of the obvious area characteristics of their connected areas. The remaining players and basketballs can be identified by the target recognition algorithm based on Hu invariant moments, so as to complete the detection of the sports targets of the players and basketballs. However, due to the large moving targets in the video and the players are very prone to occlusion, a single moving target cannot be segmented well [18].

The multi-camera cropping method based on the visual shell technology to calibrate multiple targets can effectively deal with the problems of occlusion and adhesion in the case of multiple people on the basketball court. Therefore, this paper proposes a multi-camera cropping method for basketball video. The visual shell method is currently a widely studied modeling method. This article only needs to calibrate the target object without modeling and displaying it, so only the cube cutting idea based on multi-camera is used.

In this article, because the basketball trajectory in the video is detected, in the relationship between the front and rear frames, the foreground information of the motion can be obtained through Gaussian background modeling, which includes people and balls. Through the first stage of motion foreground extraction, the area needed for circle detection is reduced to less than half of the original area [19]. On this basis, the foreground image is then eroded, and then the eroded image is subtracted from the uneroded foreground image to obtain an image that contains only foreground edge information, so that the pixels to be calculated for constructing the Hough array are minimized.

Corrosion operation is the basis of morphological processing, and usually forms the basis of many morphological algorithms together with dilation. Morphological processing in digital images is an image processing tool for the purpose of extracting image components useful for expressing and describing the shape of an area from an image. In this process, we mainly focus on the analysis of binary graphs. Since only the corrosion operation is used in the article, this article only briefly introduces the principle of the corrosion operation. The corrosion operation requires the two-dimensional binarized original image to be processed and the data matrix used for the convolution operation. The common one is a 3×3 operand matrix.

When the operand matrix moves on the pixel matrix, when the input pixel to be processed by the operand is the background pixel, the center pixel is the background pixel 0, otherwise the input pixel value under the center pixel [0, 0] remains unchanged. The foregoing preprocessing can be summarized as follows: First, perform Gaussian background modeling on the video. Since the image information to be processed is a sequence of video frames, and the background is simple, it can be approximated as static. According to the relationship between the video frames, a moving foreground binarized image is quickly obtained; then a 3×3 corrosion operation is performed on the binarized foreground, and the image after the corrosion operation is subtracted from the frame without the corrosion operation, and finally obtained the edge map of the foreground. After the above-mentioned preprocessing of the video frame, Hough transform is performed. However, directly using SHT to perform circle detection on the image requires mapping the pixels of the entire image to the parameter space and then making point-by-point judgments, which affects the efficiency and accuracy of the algorithm. Therefore, this paper proposes an improved method based on the standard Hough transform. The basic idea is to use a multi-dimensional array to replace multiple loops while reducing the dimensionality of the accumulator. At this time, we need to know the radius of the circle to be detected, that is, the radius r of the circle must fall within the range of (rmin, rmax). It is known that in the image space, a circle can have the following parameter expressions:

$$\begin{cases} x = a + r\cos\theta \\ y = b + r\sin\theta \end{cases} \quad (2)$$

In the formula, (a, b) is the center of the circle, r is the radius of the circle, and the symbol 0 is the angle between the connection line between the point (x, y) and the origin and the X axis. Correspondingly, the point in the image space is mapped to the parameter space. The formula is:

$$\begin{cases} a = x - r\cos\theta \\ b = y - r\sin\theta \end{cases} \quad (3)$$

The matching criterion is a criterion for measuring the correlation between two image blocks. The choice of matching criteria directly affects the complexity of the search process and the accuracy of motion vector estimation.

$$CCF(i,f)=\frac{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}B_k(m,n)B_{k-1}(m+i,n+j)}{\left[\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}B_k^2(m,n)\right]^{0.5}\left[\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}B_{k-1}^2(m+i,n+j)\right]^{0.5}} \tag{4}$$

Among them, $B_k(m,n)$ is the pixel value at the kth frame (m, n). When $CCF(i,j)$ is the maximum value, it means that the two blocks are most similar, and (i, j) is the corresponding motion vector.

3. Experiment of Adaptive Monitoring Method for Basketball Video Image

3.1. Database Introduction

One of the main requirements facing statistical pattern recognition and machine learning is whether there is a suitable data set. If there is no suitable data set, it is impossible to accurately and reliably evaluate related methods. Supervised learning methods require more data sets than unsupervised learning methods and semi-supervised learning methods. Unfortunately, there is no basketball video calibration data set for exciting event detection so far. In order to realize the detection of wonderful events and evaluate the detection effect of this article, this article first selects the appropriate basketball video. The game progresses faster in the basketball game. When the video segmentation is performed, the video is divided into about 10~15s segments, and the segmentation is manually calibrated. Good video clips, build sample data sets.

In order to reflect the diversity of data samples and the universality of the model, the videos that constitute the data set of this article are selected from a certain basketball game and other games. At the same time, the data set is selected from games under different conditions. Some games are played during the day and some games are played during the day. At night, in addition, the video formats are also different, mainly including MPEG format, MP4 format, AVI format, MKV format, etc., the duration is about 20 hours, the frame resolution is 352×288, the simulation software environment Matlab R2014b. The data set contains a total of 300 Video clips, including 100 goals, fouls and normal events, each with an average length of about 10s.

3.2. Experimental Design

In order to test the performance of the method proposed in this paper, this paper uses two indicators of accuracy and recall. Neural network training and behavior prediction of team members. First of all, in order to build an intelligent network, we collected a total of basketball game videos as the raw training data, and the video frame rate was 25fps. The overall level of the participating teams in these videos is roughly similar. For each game video, firstly, each player's shooting and grabbing conditions on the field are counted separately, so that each player's shooting ability and grabbing ability can be determined. According to the actual situation, the initial values of shooting ability and grabbing ability are set to 10 and 3 respectively in the experiment. The upper and lower limits of the ability to grab the ball are set to 5 and 1, respectively, and the upper and lower limits of the shooting ability are set to 25 and 1 respectively.

In the testing phase, we selected 10 basketball game videos with a frame rate of 25fps. The overall level of the participating teams in the video is roughly similar to the level of the teams in the training video. For the shot switching in basketball video, we manually cut the video into shots and analyze each shot separately.

In order to extract the basketball route. First of all, the basketball area is idealized, that is, the center point of the basketball area is replaced by the area; the coordinates of the center of the basketball in each frame of the video are counted to obtain the basketball movement track. The basketball movement speed between the game video frames used in the experiment is not fast. Therefore, we use linear interpolation to extract the basketball trajectory $y(x)$ between frames, as shown in equation (5),

$$y = y_{n-1} + C_n(x - x_{n-1}) \quad \mathrm{C_n} = \frac{y_{n-1} - y_n}{x_{n-1} - x_n} \tag{5}$$

4. Experimental Analysis and Discussion of Image Adaptive Monitoring Methods

4.1. Monitoring and Analysis of Basketball Goals and Foul Events

In the learning process of model parameters, positive samples and negative samples need to be crossed to correct model parameter learning. The main purpose of the experiment is to realize the detection of shooting and foul events in the basketball game video. The experimental database is a manually defined database. According to the database, the video clips are divided into three categories: shooting and goal clips, game foul clips and other clips (ie in addition to shooting goals and foul incident fragments other fragments). In the experiment, first divide the data, and divide the existing data into training data and test data. When learning the model parameters of each type of event, the training data needs to be divided into two parts, a positive sample and a negative sample. Take a basketball shooting and goal event as an example. Select 50 from the shot data segment as the positive sample of goals, and select 50 from the data segment other than the shot data as the corresponding negative sample. These positive and negative samples are together as training data for model parameter learning. According to the above similar method, 50 scoring segments and 50 other segments are selected from the remaining data to form the test data to detect the learning effect of the model. Table 1 shows the detection effect of the machine learning model in this paper under the condition of parameter changes. As the previous analysis, the main parameters affecting the graph structure of the probability graph model are the hidden state window length ω and the number of hidden states n. The length of the hidden state window ω determines the number of observations associated with the current state [20]. When ω=0, it means that the current state is only determined by the current observation value. When ω=1, it means that the current state is not only related to the current observation value, but also Related to the previous observation. The larger the value, the more observations associated with the current state, and the more complex the model. The number of hidden states n is defined as the number of hidden tags in the model. The more hidden states, the more accurate the model's expression and learning of the observation sequence and the more complex the model structure.

As shown in Table 1, the detection results of each event under the change of model parameters are given, and some potential laws can be found by analyzing the results. Take the shooting and goal event as an example for a simple analysis. When the number of hidden states is small, the hidden state is insufficient to express and learn the observation sequence, and it is difficult to accurately express the internal structure of the goal segment [21], such as n =1. No matter how to adjust the parameter ω, the detection accuracy of the model is always low. When the number of hidden states increases, the expression and learning ability of the hidden state on the observation sequence is enhanced. At this time, the model can better express the video clip information [22], and the detection performance is greatly improved, such as n=2, ω=0 The detection accuracy rate and recall rate reached 88.89% and 96.00% respectively; at this time, if the number of hidden states n = 2, adjust the window parameter ω appropriately, and as the value of ω increases, increase the previous observation value to the current state Enhance the correlation between the observed value and the hidden state, which can improve the detection accuracy. For example, when n=2 and ω=1, the recall rate and precision rate are comprehensively optimized. However, when the value of ω is too large, the observation value of the specific current state that is far away will have a negative impact on the expression of the current state [23], which will reduce the detection performance. When the number of hidden states is too large, the hidden states of the model will express excessively detailed video content, resulting in an over-fitting phenomenon, which reduces the detection performance. Therefore, in the process of model parameter learning for each type of event, appropriate model parameters must be selected.

Table 1. Monitoring results of many exciting events in this article

Model parameters		Shot goal		Foul	
n	ω	Recall rate	Precision	Recall rate	Precision
1	0	100	76.33	86.00	59.47
	1	100	76.33	86.00	59.47
	2	100	76.33	86.00	59.47
2	0	96.00	88.89	96.00	100
	1	98.00	94.43	100	100
	2	96.00	89.37	100	98.44
3	0	96.00	89.34	92	100
	1	100	77.68	100	97.45
	2	100	85.79	100	97.45

4.2. Analysis of Wonderful Event Monitoring Results

Table 2. Wonderful event monitoring results of this article and the comparison method

Wonderful events	Recall rate/%			Precision/%		
	Method A	Method B	Method of this article	Method A	Method B	Method of this article
Shoot and score	92.2	95.67	98.34	89.65	97.42	98.46
Foul	93.15	92.73	98.27	91.42	92.48	99.71
Average	92.68	94.20	98.31	90.54	94.95	99.09

As shown in Table 2, the experimental results of the detection framework and comparison algorithms in this paper are given. Analysis of the experimental results shows that the detection performance of this paper is better. As shown in Figure 1, compared to Method A, the average experimental accuracy rate is increased by 5.63%, and the average recall rate is increased by 8.55%. As shown in Figure 2, compared with method B, the increase was 4.11% and 4.14%, respectively. On the one hand, the reason is that the model is very suitable for the structure of the video sequence. The hidden state can associate related video frames [24]. The window parameters make the current hidden state not only limited to the influence of the current observation, but also related to the previous or previous observations. Fully express the spatio-temporal correlation between adjacent frames of the video. On the other hand, this article proposes two sequences of observation values to fully express the video data: emotional excitation feature value sequence can make full use of video image features and whistle shot value sequence can make full use of audio information.

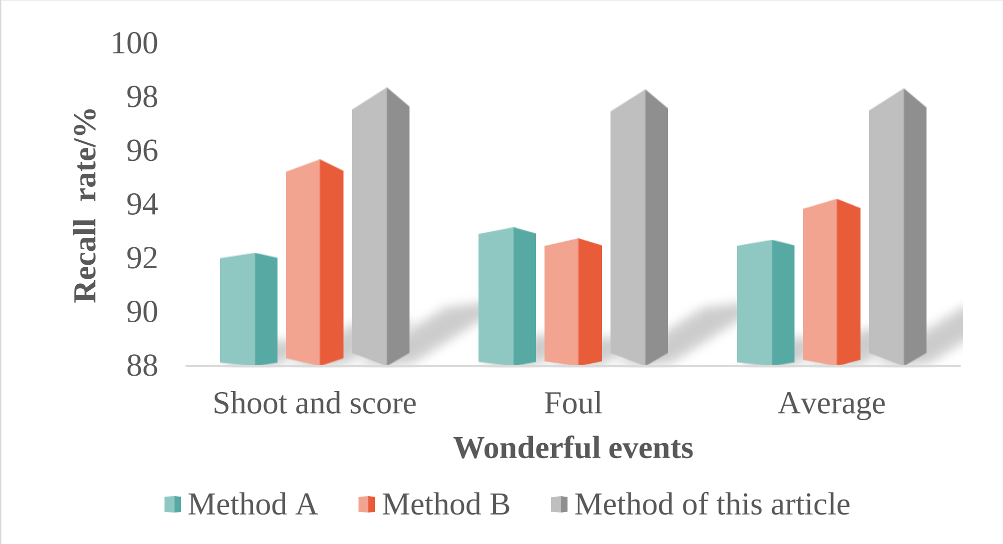

Figure 1. Comparison of basketball action recall rates

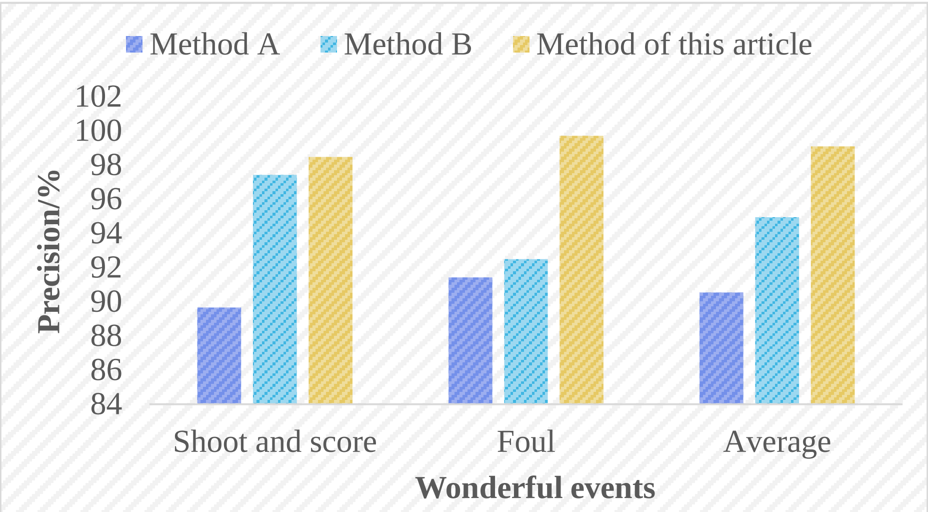

Figure 2. Comparison of accuracy rate of basketball action

4.3. Monitoring and Analysis of Basketball Shot Speed and Angle

In the shot frame T3, in order to put the ball into the basket more effortlessly, save the theoretical minimum shot speed and the corresponding best shot angle. Since the height and wingspan of the tested athletes are known, the corresponding shot height can basically be determined. Through many experiments, we take the average shot height as H=2.38m, and the corresponding free throw distance is determined to be L=4.225m. The theoretical formula can calculate the best shot angle $\theta_m = 49.51^{\circ}$, the minimum shot speed $V_m = 6.80 m/s$. Decompose V_m into vertical speed

$V_y = 5.17m/s$, $V_x = 4.42m/s$. Note: At this time, the coefficient K=0.0175.

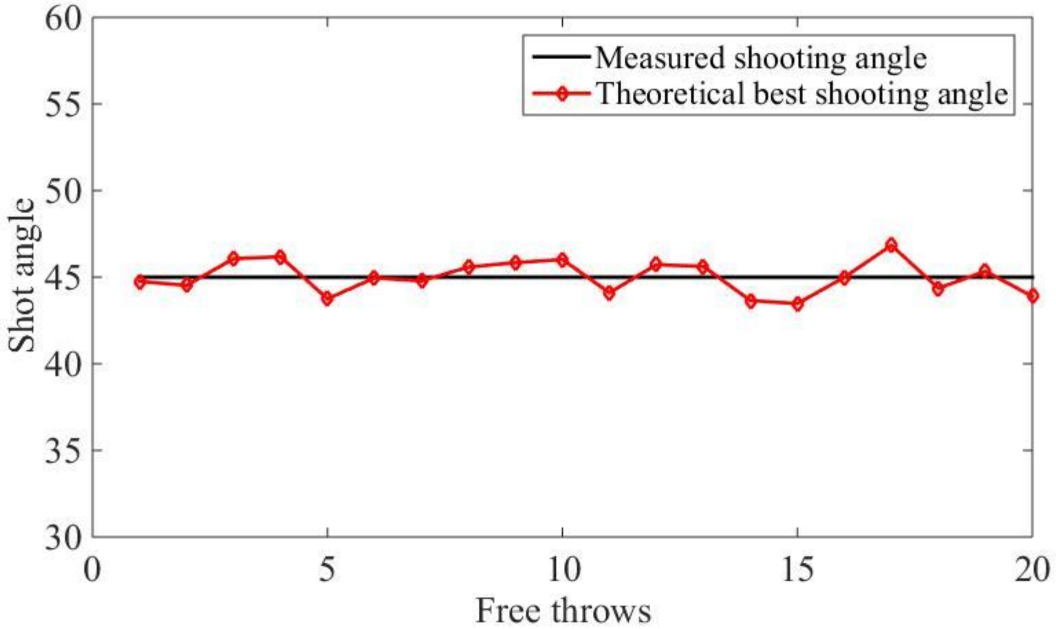

Figure 3. The shot frame acquisition result of the basketball video unit

As shown in Figure 3, professional athletes have made more than 90% free throws. This time, 20 sets of free throws made 18 sets. Obviously, the shooting angle of professional athletes is always near the best shooting angle, which is consistent with the conclusion in the paper.

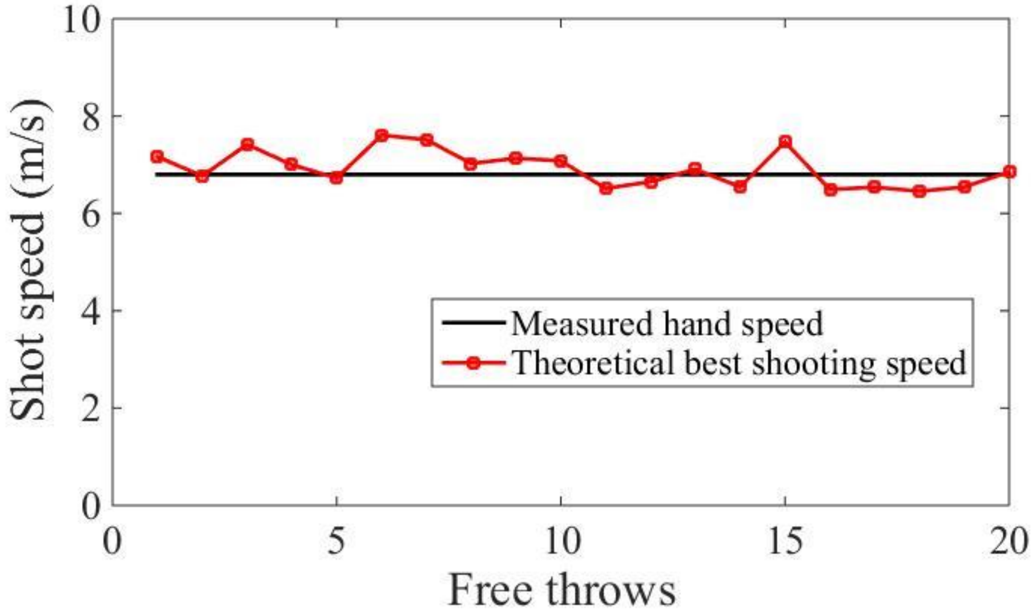

Figure 4. Video unit shot frame acquisition result

As shown in Figure 4, the shooting speed is compared with the theoretical best shooting speed.

Through the comparison, it is found that professional athletes have kept their free throws in a relatively stable area after years of repeated training. And these areas are also in the vicinity of the theoretical optimal value [25]. Through the analysis of this article, the best shooting speed can ensure that the athletes throw the ball in the most labor-saving way, and the corresponding shooting angle makes the basketball have a better shooting angle, and the error that a good shooting angle can allow is also the better [26]. Therefore, combining these two points, we can see that a good free throw technique must ensure that there is still strong stability when the physical exertion is too high during the game. The best shooting speed solves this problem, and a good shooting angle is the basketball entry. The allowable error of the basket becomes larger, which further improves the stability of the free throw.

5. Conclusion

The purpose of this research is to use modern computer technology to quantitatively analyze the tactical behavior in the competition. Through video excerpts and data statistics, to conduct statistical analysis of the players and opponents during the game, improve the on-site decision-making ability of coaches and athletes, and promote Improve the competitive level of sports events.

In the basketball segmentation research of the perspective shot, the commonly used object segmentation method based on the change area detection is very sensitive to noise, and requires the object not to move too fast. In order to correct the basketball segmentation deviation caused by the video noise and the fast basketball movement, we make corrections based on the peak characteristics of the edge gradient. At the same time, the internal and external energy calculation methods of the traditional active contour model are improved, and the judgment standard of the regional optimal solution and segmentation validity is further established.

This article studies a monitoring method for basketball players. Define a hierarchical structure composed of auxiliary features and main features. Layers are associated with the suggested distribution of particles; when players are monitored, the main feature particles are guided to move closer to the target through auxiliary features according to the relationship between the levels. To optimize and update the recommended distribution of main feature particles, make the recommended distribution of main feature particles closer to the true posterior probability distribution of the target. This method only needs a small number of high-confidence particles to represent the posterior probability distribution of the target, which reduces the amount of system calculation and improves the real-time tracking.

For the current basketball video image monitoring, a lot of manual methods are needed. This paper designs an integrated basketball video image monitoring method. This method uses the steps of collecting, enhancing, segmenting and classifying basketball video images to obtain high-precision monitoring results, which provides data support for high-tech sports research.

Funding

This article is not supported by any foundation.

Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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