Event Detection based on Hidden Conditional Random Field Model in Sport Videos

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Abstract

This paper proposes a new highlights event detection method for basketball videos. The support feature of each highlight is firstly found using the concept lattice clustering technology according to the audio-video features and middle level semantic features defined in this thesis. Then, the support features are weighted to construct the affective arousal feature. The audio shots are processed to obtain the whistle shots features using the whistle shots detection method defined in this thesis. The affective arousal feature and the whistle shots features are combined as the input. An effective HCRF (Hidden Conditional Random Field) is constructed to realize highlight detection of basketball shooting and fouls. Experimental results show the effectiveness of the proposed method.

Keywords: sport video; event detection; hidden conditional random field; video semantic analysis

(Submitted on July 8, 2018; Revised on August 12, 2018; Accepted on September 11, 2018)

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1. Introduction

The rapid growth of video data makes it more and more difficult for people to find videos of interest. Long video durations make it difficult for people to have enough time to view the full video [1-3]. Most of the time, people just want to see the parts that they are interested in. These reasons have led to the introduction of exciting event detection technology. Detection of pre-highlight events was mainly done manually. In order to reduce manpower consumption, automatic detection of highlight events was achieved and machine learning methods were adopted. Common machine learning methods include naive Bayes, conditional random fields, decision trees, logistic regression models, support vectors machine and so on. This paper compares and analyzes each classification model and uses the hidden conditional random field model (HCRF) as a classification model [4-6]. The hidden conditional random field model is a relatively novel classification model proposed by Quattoni in 2003 [7]. It was formed by introducing hidden variables based on the CRF model. The HCRF model is a graph structure that can model complex and changeable spatial information in videos by the mesh structure model, and it can integrate temporal information and spatial information through hidden status nodes, thus analyzing and expressing the video content in time and space [8].

In recent years, the number of basketball fans has increased rapidly and has almost surpasses the number of football fans, becoming the most popular sport [9]. Thus, this paper analyzes basketball videos. First, basketball highlight event detection frame is given in this paper; then, illustrations are made on the fundamental theory of the HCRF model, and comparisons between common machine learning methods are given. Next, goal and foul events in basketball videos are researched and analyzed, leading to the introduction of the inference process of the HCRF model for event detection, which accurately achieves the detection of two events. Finally, a brief introduction and the analysis of experimental results of the empirical data are given.

2. Correlation Theory of Hidden Conditional Random Field (HCRF)

HCRF is the introduction of hidden state variables on the basis of the CRF (Conditional Random Field) model. Both HCRF

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and CRF are probabilistic graphs, that is, the probability model of the conditional dependence relation between each variable is represented by the graph, which is the combination of probability theory knowledge and graph theory knowledge.

In the probability graph, a random variable is represented by a node, and a dependent variable is connected to each other by the edge. According to whether there is a direction in the graph, it can be divided into directed graph and undirected graph. Hidden Markov Model (HMM) is a directed graph probability model, which introduces the hidden state in the Markov chain, i.e., it is not convenient to observe the state.

Random Field is a sample space \((y_1, y_2, \ldots, y_n)\) formed by a set of random variables. The relationship between random variables is not restricted, that is, the variables may be dependent on each other, but when these variables are dependent on each other, it is only practical to take these variables out separately. The addition of Markov restrictions on the rules of the random field forms the Markov Random Field (MRF).

The Markov property is that in the distribution of all variables in a given field, any random variable should satisfy the following relation, and it is shown in Equation (1).

\[
P(y_i | Y_{\neq i}) = P(y_i | N(y_i))
\]

Markov is the micro property of MRF, and the joint distribution is the macroscopic property of MRF. Suppose that the set of variables of the known MRF is \(Y = (y_1, y_2, \ldots, y_n)\), then the set of dependencies between variables is \(C_G\). Then, the joint distribution is Equation (2):

\[
P(Y) = \frac{1}{Z} \prod_{x \in C_G} \Phi_x(y_x)
\]

CRF is used to add observation values under each variable in MRF to form a new probability graph distribution. It is determined that the joint distribution probability model in a given observation concentration is the process of solving CRF. Suppose that the observation sequence of CRF is \(X = (x_1, x_2, \ldots, x_n)\). The state set is \(Y = (y_1, y_2, \ldots, y_n)\). The probability of the labelling condition of the vertex can be derived from the following Equation (3) and Equation (4).

\[
P(Y | X, \theta) = \frac{1}{Z(x)} \exp \left( \sum_{i=1}^{n} \sum_{a} \theta_a f_a (y_i, y_i, x_i) \right)
\]

\[
Z(x) = \sum_{a} \exp \left( \sum_{i=1}^{n} \sum_{a} \theta_a f_a (y_i, y_i, x_i) \right)
\]

The HCRF model is the extension of the CRF model. By introducing the hidden state layer, the observation value and the state variable are expressed more fully, forming a new probability graph model. HCRF can be regarded as a special CRF model, and the conditional distribution model of HCRF is similar to that of the CRF model.

Suppose that the set of observation sequences is \(X = (x_1, x_2, \ldots, x_n)\), and \(x_i\) represents the \(i\) observation sequence. \(Y = (y_1, y_2, \ldots, y_n)\) is the result of predicting the set of tags. \(y_i\) is a prediction label for the \(i\) observation sequence \(x_i\).

The set of hidden states is represented by \(S = \{s_1, s_2, \ldots, s_j\}\), which is determined by the current state or a few adjacent states for an arbitrary hidden state variable \(s_j\). It can be determined by window \(\omega\) that when \(\omega = 0\), the implicit variable is determined only by the current observation value \(x_i\). When \(\omega = 1\), the hidden variable is determined by the current observation value \(x_i\), the previous observation value \(x_{i-1}\) and the latter observation value \(x_{i+1}\). According to the theory of the random field, the joint probability distribution of the predicted label can be expressed in the following Equation (5):
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\[ P(y | x, \theta, \omega) = \sum_i P(y, s | x, \theta, \omega) = \sum_i \exp(\Phi(y, s, x, \theta, \omega)) \]

(5)

The parameters \( \omega \) of the HCRF model are composed of \( \theta(s), \theta(y, s), \theta(y, s, y) \), so these parameters can be further expressed as \( \theta = [\theta(s), \theta(y, s), \theta(y, s, y)] \). If the total number of observation sequences of the training is \( N \), the expression of the likelihood function of the objective function is \( L(\theta) \). It is shown in Equation (6).

\[ L(\theta) = \sum_{i=1}^{N} \log(P(y_i | x_i, \theta, \omega)) = \sum_{i=1}^{N} \log(\sum_{s \in S} \exp(\Psi(y, s, x, \theta, \omega))) \]

(6)

According to the maximum likelihood function, we can figure out the model parameter \( \theta^* \). It is shown in Equation (7).

\[ \theta^* = \arg \max_{\theta} L(\theta) \]

(7)

The training model parameters can be used to predict the unknown data, and a new fragment can be used to obtain its prediction label by using the generalized confidence propagation algorithm. Suppose that \( x \) is the input sequence, and the predictive category label is \( y^* \). It is shown in Equation (8)

\[ y^* = \arg \max_{y \in Y} P(y | x, \theta^*, \omega) \]

(8)

HCRF is an extension of CRF and overcame the assumption of the independence of variables in the Markov chain. The structure of HCRF is very similar to that of the video, and a video can abstract specific events. Therefore, the spatial and temporal structure of a video can be simulated with the network structure of HCRF. This paper will use this model as a classification prediction model to detect the goals and fouls in the basketball game.

3. Basketball Goals and Foul Event Detection

3.1. Wonderful Event Detection Framework

Videos can be divided into two parts according to content: video image stream and audio stream. This paper conducts analysis on the two parts respectively. First, the audio data and video image data of live videos are obtained through relevant software processing, energy feature, and whistle detection. Other features of short-time audio are extracted, some of which are used for shot segmentation while others are used for speech semantic extraction. Second, analyze the hierarchical structure of the video and extract relevant image features for shot segmentation and video semantic cue extraction. Finally, combine the generated audio semantic cue and video semantic cue as the input of the evaluation model and as the evaluation analysis feature to realize highlight event detection.

3.2. Supporting Feature Set Filtering

Supporting features refer to features that play major roles in each type of highlight event and have the strongest evaluation capability. This paper adopts the concept lattice clustering method to analyze the relationship between basic detection features and highlight events defined in the paper, hoping to find a potential dependency relationship between basic feature attributes and highlight event objects. Set models for basketball goal events and foul events through a concept lattice clustering method to find the supporting feature set of each.

Adopt the concept lattice clustering method [10] to conduct supporting feature analysis. Then, build a concept lattice attribute and conduct binarization on each attribute feature in order to facilitate the analysis. It is shown in Equation (9) and Equation (10).

\[ attribute_i = \frac{1}{n_{att}} \sum_{b \in att} attribute_i(b) \]

(9)
Different types of highlight events have different combinations of supporting features, that is to say, that they may be sensitive to some of the attributes but insensitive to others. Therefore, to obtain the common sensitive feature of the same types of highlight events, enhancing the detection performance of such events and magnifying the evaluation capability of the feature, recall rate and the comprehensive evaluation index combined with it are adopted to determine if each attribute feature can be regarded as a supporting feature of such a highlight event. The evaluation criteria is shown in Equation (11) as:

\[ \text{Rule}_{e,f} = \text{precision}_{e,f} \times 0.5 + \text{recall}_{e,f} \times 0.5 \]  

(11)

3.3. Middle Level Semantic Extraction

3.3.1. Construction of Emotional Incentive Features

The emotional motivation model was proposed by Hanjalic Alan [11], who was hoping to endow some semantics to the low and middle-level feature, as well as map semantics to a coordinate system that consists of three related independent emotional attributes: the emotional motivation dimension, emotional attraction dimension and emotional control dimension. Then, we understand and express videos through an analyzing emotional motivation model. This paper uses the above-selected supporting feature to conduct the construction of an emotional motivation model. The value of an emotional motivation model adopts the following Equation (12).

\[ \alpha_u = \lambda_1 \times F_{a1} + \lambda_2 \times F_{a2} + \lambda_3 \times F_{a3} + \lambda_4 \times F_{a4} \]  

(12)

\( \alpha_u \) represents the emotional incentive eigenvalues obtained by supporting the feature combination of class \( u \) exciting event. \( F_{a1}, F_{a2}, F_{a3}, F_{a4} \) are the four supporting features of the wonderful event of class \( u \). \( \lambda_1, \lambda_2, \lambda_3, \lambda_4 \) are the weight corresponding to four supporting features, respectively, which is used to indicate the importance of the support feature to detect this kind of event. The larger the value, the more important it is for this kind of event. Their values are obtained by making statistics on fragments of each type of event. It is shown in Equation (13).

\[
\left\{
\begin{array}{l}
\alpha_i = \frac{\text{mean}_{-H_i} - \text{mean}_{-N_i}}{\text{mean}} \\
\lambda_i = \frac{\alpha_i}{\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4}
\end{array}
\right.
\]  

(13)

3.3.2. Whistler Sound Detection (WSD) for Shot

Whistler sound detection can assist part of the particular event detection very well. This paper uses it as one of the features of wonderful event detection. The occurrence of foul events in basketball matches is often accompanied by a whistle; therefore, whistle detection has become one of the major contents of foul detection. This paper adopts the semantic feature of whistle shot to improve the accuracy of whistle detection. Whistle shot mainly begins with audio to analyze the feature of audio information, and its extraction process is shown in Figure 1. First, use relevant software to separate the audio from the video, like video shot grouping. Here we choose the audio frame based on n frame as a group to conduct detection. When the \( k \) frame is reached, conduct whistle detection first. If there is no whistle in the \( k \) frame, then input the \( k + 1 \) audio frame. If there is a whistle in the \( k \) frame, then detect whether the \( k + 1 \) audio frame includes a whistle. When there exist whistles in 5 consecutive audio frames, then mark the shot as a whistle shot, otherwise, mark it as a non-whistle shot.

3.4. Model Reasoning and Implementation Steps

On the basis of fully analyzing the content of the basketball matches, this paper conducts extraction on the low-level feature of goal events and foul events detection from two aspects: audio and video. We use the extracted feature to abstract the middle-level semantic feature of the event detection. The input and output of the model are the foundation of highlight event detection. The input observation sequence and label set used in this paper are defined as follows.
**3.4.1. Data Sample Set Construction**

Taking the goal event in the basketball game as an example, the definition of the sample set in this paper is given:

1) Firstly, the video image and audio separation of the video are realized, respectively, which constitute the corresponding video image data stream $V$ and audio data flow $D$.

2) The processed audio data stream and video image data stream are segmented, and at the same time, a set of 15 frames is used in the shot, which is further divided into the processed audio frame group and video image frame group. The video data stream and the audio data stream can be further expressed as $V = \{v_1,v_2,\ldots,v_n\}$ and $D = \{d_1,d_2,\ldots,d_n\}$.

3) The frame group $V = \{v_1,v_2,\ldots,v_n\}$ of the video image was extracted.

For each video image frame, Edge Ratio ($ER$), Shot Exchanging ($SE$), Field Ratio ($FR$) and shot Moving Intensity ($SMI$) are extracted. The features of each frame of the frame group $d_i$ of a video image are composed of four features, namely, $v_i = [ER, SE, FR, SMI]$.

4) The video frame group emotion excitation value features are extracted, and the extracted image video frame group calculates each frame group $v_i$ emotional incentive value $a_i$ according to Section 3.2. The emotional value of the video can be expressed as $A = \{a_1,a_2,\ldots,a_n\}$.

5) The feature extraction of video audio frame group $D = \{d_1,d_2,\ldots,d_n\}$ and the sound detection of each audio frame in the audio frame group can get $d_{ij} = [WSD]$. According to the detection method of whistle shot in Section 3.2, when there are five consecutive audio frames in the audio frame group $d_j$, the whistle shot value of the frame group is 1. So, at this point $e_i = 1$, and $e_i$ represents the whistle sound shot value of the $i$ audio frame group. Otherwise $e_i = 0$. For each group of audio frames, the whistler sound shot can get the observation sequence of the whistle sound shot: $E = \{e_1,e_2,\ldots,e_n\}$.

6) The observation sequence is formed by combining Steps (4) and (5). The observation sequence can be further expressed as $X = \{x_1,x_2,\ldots,x_n\}$.

This paper mainly realizes the shooting goal, game fouls and normal segments, so the sample tag set can be defined as
3.4.2. Model Reasoning and Implementation Steps

1) There is no suitable database in the construction of highlight event dataset in basketball matches. Therefore, this paper adopts manual interception video and manual calibration to form a sample set. When conducting the experiment, select $N_1$ goal shots, $N_2$ foul events, and $N_3$ other shots of the basketball matches from the total set according to the category. The feature datasets of each type of event are formed according to the middle feature extraction, which is expressed as $V_{t,s} = \{V_{t,s,1}, V_{t,s,2}, \ldots, V_{t,s,n}\}$.

2) Feature screening. Use the clustering method based on concept lattice to set models for each event and to obtain the exclusive feature combination of each event by clustering analysis. First, conduct data pre-processing on the data feature set $V_{t,s}$ obtained in the previous step and use the event to be detected as the concept lattice clustering theme to conduct concept lattice analysis and clustering screening to obtain all major feature supporting groups of each event $C_s = \{C_1, C_2, C_3, C_4\}$.

3) Build input feature. First, separate the audio and video images in the video to form a video-audio dataset and video image set, and set observation sequence $X_s$, including emotional motivation value feature sequence $A_s$, whistle shot value sequence $E_s$ and category label set $Y_s$, which are used for basketball highlight event training and prediction according to the construction method of the sample input set and label set. The basic dataset is formed by matching the observation sequence with a label one by one, which can be used for the training and prediction of the HCRF model.

4) Build a training dataset for exciting event detection. Step 3 observation sequence $X_s$ and class label $Y_s$ constitute the training dataset $\{X_s, Y_s\}$, $s = 0, 1, 2$.

5) Training and learning of model parameters. Learn model parameters after the preparation of training dataset. The HCRF model is a probability map model, the probability distribution of which is influenced by the correlation between the number of status variable and the status. The main parameters influencing these two factors are the hidden status amount $n$ and hidden status window length $w$. For any particular highlight event $s$, it is necessary to manually set those two parameters repeatedly when learning the optimal parameter to obtain the optimal model structure and best model parameters of the best highlight event.

6) New highlight event prediction. Like most machine learning models, the aim of the HCRF model is to use the learned model parameters to predict the category of unknown highlight events. For a new highlight event clip $M$, the category label of the event clip is uncertain, so first extract the audio stream feature and video image stream feature of the new highlight event clip, and then calculate the emotional motivation value sequence $A_s$ and shot value sequence $E_s$ of the highlight event. Input the above two sequences into an event detection model that has been learning a good model parameter $\theta_{t,s}, s = 0, 1, 2$. Use the BP (Belief Propagation) algorithm to calculate the segment corresponding to the trained wonderful event likelihood probability value of the model.

4. Experimental Results and Analysis

4.1. Experimental Environment and Experimental Data

In order to achieve the wonderful event detection and to evaluate the paper detection effect, this paper selected a suitable basketball video. The video is divided into segments of 10~15s, and the segmented video fragments are manually demarcated to set up the sample data set. In order to embody the diversity and universality of data samples, the video of this dataset is selected from the 2017 NBA playoffs, 2016 NBA pre-season, 2015 CBA and 2008 Olympic Games. At the same time, the data set is selected from different conditions, part in the daytime and part during the night. In addition, the format of the videos are different, including MPEG, MP4, AVI, MKV and so on. The time length is about 20 hours, and the frame resolution is $352 \times 288$. Simulation software environment is Matlab R2008a. The data set contains 300 video clips, including 100 goals, fouls and normal events. The average length of each fragment is about 10s. In order to test the performance of the proposed method, this paper uses the accuracy rate and the recall rate to measure the two indexes, and the two indexes can be calculated by the next type. It is shown in Equation (14) and Equation (15).
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\[
\text{Precision rate} = \frac{\text{Number events of detection correct}}{\text{The total number of events}}
\]  
\[\text{(14)}\]

\[
\text{Recall rate} \equiv \frac{\text{Number events of detection correct}}{\text{The number of events associated with the event}}
\]  
\[\text{(15)}\]

4.2. Wonderful Event Detection

The HCRF model is a supervised machine learning model. In the learning process of model parameters, the inter-cross of positive samples and negative samples is needed to correct the model parameter learning. The main purpose of the experiment is to achieve the detection of goal events and foul events in basketball videos. The experimental database is a manually defined database, which will be divided into three categories according to video clips: goal clips, foul clips and other clips. When conducting the experiment, first divide the data and then separate the existing data into training data and test data. It is needed to divide training data into positive samples and negative samples when performing model parameter learning of each event. Take the goal events as an example, select 50 samples from the goal data clips as positive samples, and select 50 samples out of the goal data clips as negative samples. Both the positive and negative samples are regarded as the training data in HCRF model parameter learning. Similarly to the above method, select 50 goal clips and 50 other clips from the remaining data to form test data to detect the learning effect of the detection model. Figure 2 shows the sequence of key frames in the wonderful event fragment. Table 1 shows the detection effect of the HCRF machine learning model in the case of parameter change.

![Figure 2. The detection diagram of the wonderful event in this paper](image)

<table>
<thead>
<tr>
<th>Model parameters</th>
<th>Shooting a goal</th>
<th>Foul</th>
</tr>
</thead>
<tbody>
<tr>
<td>(n)</td>
<td>(\omega)</td>
<td>Recall rate (%)</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>100</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>96</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>96</td>
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<td></td>
<td>2</td>
<td>96</td>
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<tr>
<td>3</td>
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<td></td>
<td>1</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>100</td>
</tr>
</tbody>
</table>

As in the previous analysis, HCRF is a probabilistic graph model, and the main parameters that affect the structure of the probability graph model are the length of the hidden state window \(\omega\) and the number of hidden states \(n\). The hidden state window length \(\omega\) determines the number of observed values associated with the current state. When \(\omega = 0\), the current state is determined only by the current observation value. When \(\omega = 1\), the current state is not only related to the current observation value, but also related to the previous observation value. The larger the \(\omega\) value, the more the current state
associated observations are and the more complex the model is.

Table 1 shows the detection results of each event under the variation of model parameters. Some potential laws can be found through analyzing the results. Take the goal event as an example:

1) When the number of the hidden status is small, the expression and learning of the hidden status to the observation sequence is sufficient, which makes it difficult to accurately express the internal structure of goal clips. When \( n=1 \), adjust parameter \( \omega \). The detection accuracy of the HCRF model is always lower.

2) When the number of the hidden status increases, which means the expressing and learning capability of the hidden status to the observation sequence is enhanced, that is when the HCRF model can express the video clips information well and the detection performance is greatly improved. When \( n=2 \) and \( \omega = 0 \), the detection accuracy and check rate were 88.89\% and 96.00\%, respectively. At this point, if the number of hidden states is \( n=2 \), adjust the window parameters \( \omega \) appropriately. The detection accuracy can be improved as we increase \( \omega \); that is, to increase the impact of previous observation on the current state and the incidence relation between the observed value and hidden status. For example, when \( n=2 \) and \( \omega = 1 \), the recall rate and the precision rate would colligate to reach optimization. However, if the \( \omega \) value is too large, the observation value, which is far away from the current status distance, would have a negative influence on the expression of the current status, which would degrade the detection performance.

3) When the number of hidden status is too large, it would result in the over-specification of the HCRF model on the hidden status video contents and lead to the over-fitting phenomenon, which would degrade the detection performance. Therefore, proper model parameters must be chosen in every HCRF model parameters learning process of the events.

Table 2 shows the experimental results of the detection frames and the comparison algorithms in this paper. By analyzing the experimental results, it can be found that the detection performance described in this paper is better. Compared to literature [3], the average accuracy is improved by 9.30\% and the average recall rate is improved by 5.8\%; compared to literature [6], the above data are improved by 1.67\% and 2.33\%, respectively. The reason is that HCRF is very suitable for the video sequence structure. The hidden status can be correlated to relevant video frames and window parameters keep the current hidden status from the influence of the current observed values as well as correlate it with the former observed values, which can fully express the spatiotemporal correlation between video frames. In addition to that, this paper proposes two observed values to fully express the video data: emotional motivation feature value sequence, and whistle shop value sequence, which can make full use of video image features, and whistle shop value sequence, which can make full use of audio information.

<table>
<thead>
<tr>
<th>Wonderful event</th>
<th>Recall rate %</th>
<th>Precision rate %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shoot a goal</td>
<td>Literature[12]</td>
<td>92.20</td>
</tr>
<tr>
<td></td>
<td>Literature[13]</td>
<td>95.50</td>
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<td>Literature[13]</td>
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<tr>
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<td>99.00</td>
</tr>
</tbody>
</table>

5. Conclusion

Based on the HCRF model, this paper presents a new framework for the detection of basketball highlights, which has the following characteristics. By using the idea of concept lattice, this paper classifies the theme of the concept lattice and defines its supporting characteristics for each kind of event. The features are analyzed and extracted from two directions: the video-audio data stream and the video image data stream. We constructed the sequence of emotional incentive eigenvalues and whistle shot values respectively, and combined the sequence of emotional inspired eigenvalues and whistle shot values as observed values of the HCRF model, which enriched the expression ability of input features. An effective basketball goal and foul detection model has been established, making full use of the structural information and temporal and spatial information of the video, realizing the simultaneous detection of multiple exciting events. Through the analysis of the experimental results, we can fully obtain the effectiveness of the framework.

References


Yuanhui Li received his M.A degree from the University of Canberra. He is a lecturer at Heilongjiang University. His research interests include physical education, sports training and sports humanities.