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Semantic Analysis of Structured High-definition MPEG-2 Soccer Video Using Bayesian Network

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ABSTRACT

Recently, the Bayesian network has been applied for semantic analysis for soccer video games. Although existing works are intuitive to yield adequate results, they lack of scalability and robustness. Most of these works are mainly to extract features in pixel-domain by using image processing methods. However, their systems are limited to Low-definition video games as a direct consequence of slow computing speed. This paper introduces a flexible and scalable scheme to structure High-definition soccer videos by using the parameters embedded in MPEG codec, and a real time highlight scene detection system with Bayesian networks.

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1. INTRODUCTION

Sports videos have been broadcasted to large audiences for their daily life entertainment. A flexible and scalable way to manage the sports video is demanded; for instance, automatic and real time sports video summarization. Obviously, the main gap between low-level media features and high-level concepts needs to be bridged.

There exist a number of related works in this research area. Related works mainly lie in sports video analysis including soccer and various other games, and general video segmentation. For soccer videos, prior works have focused on shot classification [2], video reconstruction [4] and rule-based semantic classification [5]. Some other methods based on Bayesian networks (BNs). [6] have been also applied for semantic analysis. In [7], Sun *et al.* used BNs for scoring event detection in soccer videos based on six different low-level features including gate, face, audio, texture, caption and text. Shih *et al.* [8] developed so-called multilevel semantic network (MSN) to interpret the highlights in baseball game video. Another highlight detection method [9] exploits visual cues estimated from video streams, the currently framed play-field zone, player's positions, and the colors of players' uniforms. [10] proposed an effective algorithm for soccer videos, which detects the plays and breaks in soccer games by motion and color features.

In this paper, we present new algorithms for soccer video structure analysis. By our structure, we are primarily concerned with a temporal sequence of the *high-level* concepts, namely three kinds of events: *replay scene*, *goal scene* and *event scene*. In the *middle-level* layer, seven kinds of meaningful content shots are classified. In the *low-level* layer, some effective features are arranged. Given a video in specific domain, we aim to extract the *low-level* features and interpret the input video in terms of *high-level* concepts. Our final goal is to extract and present the meaningful information for viewers.

As shown in Figure 1, our system consists of two components; the training stage and the testing stage. In the training stage, to aim at video structure analysis, the shot change detection was carried out, and then seven kinds of shots are classified by extracting some features embedded in MPEG video codec. At the same time, three kinds of scenes are defined: *replay scene*, *goal scene* and *event scene*. Our method exposes hierarchical structure of soccer videos, and soccer video was abstracted into three levels, from high-level to low-level: the *Scene layer,* the *Shot layer* and the *Evidence layer*. Main gaps between low-level features and high-level concepts are bridged by BNs.

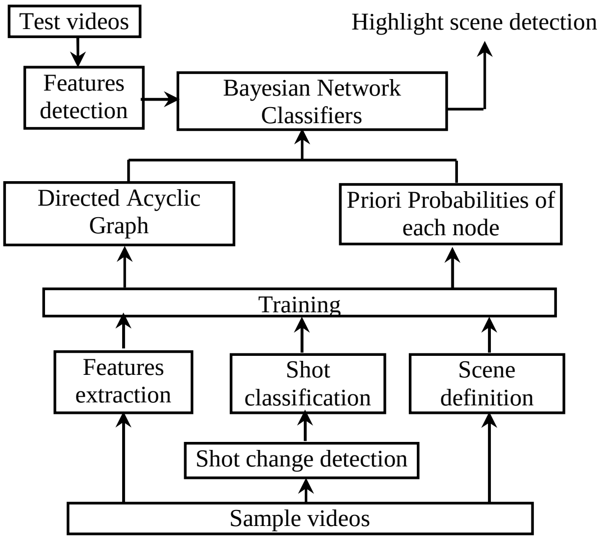

Figure 1. System flowchart

Based on the posteriori probabilities of all the concepts, given that some evidences detected out; a particular highlight scene can be estimated. Given a video in MPEG-2[13] domain, we aim to extracting the low-level features and interpret the input video in terms of high-level concept. This approach is distinctive from existing works, most of which focus on the detection features in pixel domain by purely image processing method and inaccurate boundary of detected scenes. The advantages of adapting MPEG-2 codec data and parsing structures separately from event detection are as follows; (1) by extracting and managing needed data from MPEG codec directly, computing time is decreased when extracting features for each frame, and thus, our scheme provides a real-time high analysis speed for high-definition (1440×1080 resolution) soccer video , and (2) specific shot classification is carried out after accurate shot change detection, which is powerful for the semantic analysis of highlight scene.

2. BAYESIAN NETWORK

Bayesian probability theory is a powerful tool for constructing models of phenomena involving uncertainty. Probabilities express degrees of plausibility or likelihood on a scale ranging from certainty through impossibility.

A Bayesian network [11]for variables Z is a pair(G, Θ), where G is a directed acyclic graph (DAG) over variables Z, called the network structure, and Θ is a set of CPTs(Conditional Probability Tables), one for each variable in Z, called the network parameterization. Given a directed graph (V, E), whose nodes V represent the random variable X= $\{x_1, x_2, \dots, x_N\}$ and edges E represent the conditional independent probabilities between the nodes.

To complete BNs for our soccer video program, we need to define two sets of parameters: (1) Observation probability $P(y_t|x_t)$ that specifies dependency of observation nodes regarding to other nodes in the same state. Initial probability P (x_0), that brings the priori probability distribution in the beginning of the process.

In section 3, shot change detection is discussed for video structure, and further on for BNs constructions. In section 4, we introduce our training method to build the BNs for each kind of highlight scene.

3. VIDEO STRUCTURE

To realize highlight scene detection in soccer games, the precise boundary of one scene should be identified in advance. Also, shot change detection is the basic step for high-level concept recognition, such as goal detection. Last, the Shot change detection is the fundamental task in content-based analysis and indexing of videos, as it helps us to provide a hierarchical structure of video and enables the extraction of meaningful highlights from such a structure. Under the precise shot change detection and shot classification, video structure can be precisely classified into three layers: *Scene layer, Shot layer* and *Evidence layer*.

3.1. Shot change detection

In general; shot change is defined to be an image content change between two consecutive frames. We apply standard GOP (Group Of Picture) structure[13] to our research. One GOP consists of three kinds of frame types: I frame, B frame and P frame. The order of frame types in a standard GOP is as follows: I B B P B B P B B P B B P B B. Moreover, MB (Macro Block)[13]can be divided into four types; Intra prediction (I mode) MB, Forward prediction (F mode) MB, Backward prediction (B mode) MB, and Bidirectional prediction (BI mode) MB. These prediction methods are explained in [13]. For the sake of high computing speed of further video structure, MBT method [3] is adapted for shot change detection in our paper. The proportion of each MB type in one frame is different, that has relationships with shot changes.

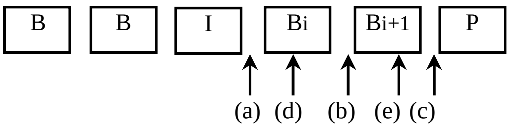

Figure 2. Shot change position

3.1.1. Patterns of Macro-block (MB) types in abrupt transition

In this paper, we classify abrupt transition into five situations (shown in Figure 2), and take MB type information in two consecutive B frames (B_i, B_{i+1}) into consideration. We mainly focus on abrupt transitions detections. Five types of abrupt transition are classified as: (a) scene change occurs before B_i frame, (b) scene change occurs between Bi and B_{i+1} frame, (c) scene change occurs after B_{i+1} frame, (d) scene change occurs at Bi frame and (e) scene change occurs at B_{i+1} frame.

3.1.2. Processing method

Due to abrupt transition happening in each kind of position discussed above, the MB prediction directions are varied. Therefore, the MB types and their proportions in two consecutive B frames are different. Our processing method for detection abrupt transition is as follows:

First, considering condition of macro-block type in P frame or B frame, we classify the frames into seven types, labeled from 0 to 6 (as shown in Table1). Then, according to patterns of MB types in abrupt transitions, we obtain a conclusion. For two consecutive B frames (B_i, B_{i+1}), if the frame types of them belong to a certain type, a shot change occurs.

Table 1. Decision rules of frame

Frame type	Conditions	
0	Number of F mode MB is the largest in B frame	Number of (B mode +I mode)MB <450
1		450≤Number of (B mode +I mode)MB<1150
2		1150<Number of (B mode +I mode)MB
3	Number of B mode MB is the largest in B frame	Number of (F mode +I mode)MB<450
4		450≤Number of (F mode +I mode)MB<1150
5		Number of (F mode +I mode)MB>1150
6	Number of I mode MB is the largest in B frame	

3.2. Main features extraction

Most of the semantic analysis methods rely on the low-level evidence in the scene. Here, we briefly describe the methods to identify the probability of the existence of the low-level evidence including 16*8 size prediction MB, Field line slope and Score board. The feature extraction process provides low-level evidences based on different media components of soccer game videos. These low-level evidences are essential for the BN. Here some main features extracting are introduced as follows:

A. 16*8 size Macro-block

To avoid the time-consuming overhead of image processing frame-by-frame, MPEG-2 codec data was used directly for Up/Long shots localization. In MPEG video codec, a practical and widely-used method of motion compensation is to compensate for the movement of rectangular sections or ‘blocks’ of the current frame. In MPEG-2 video compression standards, the 16*8MBs frequently occur especially when the camera view close up to a player and an active motion occur. Figure 2 shows the 16*8 size MB occurs in *Long Shot*(the left) and *Up Shot*(the right), labeled red block is 16*8 size MBs. We can clearly see that, in the right picture, large number of 16*8 size MBs occur because of the sharp movement of players. On the other hand, only a few 16*8 size MBs appear in *Long Shot* (shown in the left picture of Figure 3) because the motion in *Long Shot* is almost by the camerawork movement. By using 16*8 size MBs embedded in MPEG-2 coded, *Up/Long shot* can be detected rapidly from HD video without any image processing approach.

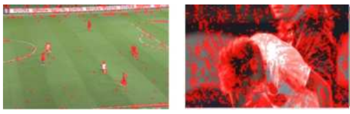

Figure 3.The 16*8 MB in Up/Long shot

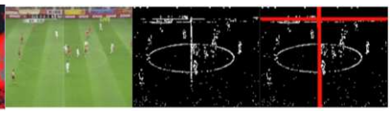

Figure 4.Extracted touch-line and half-way line

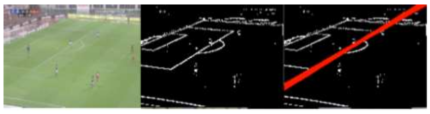

Figure 5.Extracted field-line

B. Field Line Slope

The appearance of field lines in a Long shot view can be used to indicate the occurrence of the goal gate. In other words, the appearance of gate and field lines is highly co-related. The gate is visible when the players appear close to or within one of the penalty boxes. This information of parallel lines indicating the penalty box is very useful for gate detection. The information of the field line is more reliable than the information of the gate post from the video scene, since the gate post detection may fail due to the cluttered background pixels.

From the I frame the luminance (Y) of ground and the line, chrominance (Cb, Cr) and AC component (AC qt) of the luminance (Y) are calculated to extract the MB of the field line by setting the threshold:

$$65 \leq Y \leq 235 \text{ and } 90 \leq Cb \leq 129$$
$$\text{and } 105 \leq Cr \leq 130 \text{ and } 4 \leq ACqt \leq 20$$

For Long Shot, in most situation, a camera is shooting from the stand area. As a result, the touch-line or half-way line which are only in vertical direction (Shown in Figure4). On the other hand, the Goal line or Penalty line appears in the scene when the camera is shooting the corner or near the goal area. During these situations discussed above, these lines are either vertical or oblique. By means of a method proposed in [12], binary images are transformed directly from the MPEG-2 compressed images, and then field line is extracted by using the Hough transform. See Figure5 shows the binary image and detected field line.

By extracting the field line of the ground, the slope can be computed. During one shot, the slope of the field line in the first GOP and Last 3 GOP are used to classify the Long shot into five kinds: First Goal Long shot, Last Goal Long shot, First and Last Goal long shot and Center long shot.

Figure 6. Score board disappeared during Replay Scene

Figure 7.Detected out score board

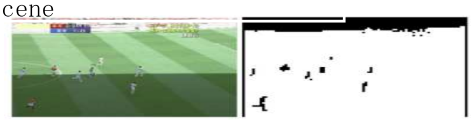

Figure 8.Extracted ground region

C. Score Board

In broadcast sports videos, a superimposed scoreboard is used to display game status such as team names, score etc. to increase the audiences' understanding of the game progression. During soccer games, the time or the score board always appears, but they disappear during a Replay scene (shown in Figure6). Therefore, by detecting the score board location and the duration of its disappearing time, it is possible to contribute the detection of Replay scene.

Our method utilizes the DCT coefficients and Motion Vector extracted from MPEG-2 codec. The area in one frame with non-motion vector and the absolute value of DCT coefficients which added up over a thresholds, which is recognized as candidate score board area. Then, the score board candidate area will be landed to the candidate list when the situation set above is satisfied over several consecutive frames. Finally, the candidate list is labeled with color as detected score board area (shown in Figure 7).

D. Average Ground Color MB number

For extracting the ground region, some feature are considered by extracting the code data from MPEG-2, the DC component of chrominance (Cb, Cr) and AC component of Cr are utilized. By setting a proper color thresholds, the ground area can be extracted out, which includes some ground color MB defined (Shows in Figure 8, the white blocks are the ground color MB).

In the Up Shot, especially when camera shoots to the audience, the camera work motion is very small. As a result, the 16*8 MB information as the only feature to detect the Up shot here is always invalid. At this time, average ground color MB number can be utilized to detect this kind of Up shot.

3.3. Shot Classification

After the shot change detection, some key features are arranged for shot classification as follows:
C0:The average ground color MB number in one shot.
C1: The average field line slope in I frames of the first one GOP in one shot.
C2: The average field line slope in I frames of the last three GOPs in one shot.
C3: The average field line slope in I frames of the first and last three GOPs in one shot.
C4: The count of shot changes in a shot without score board.
C5: The average macro block number of ground area in Iframes of the last three GOPs in one shot.
C6: The duration of one shot.
C7: The average 16*8 size MB number in one shot.
C8: Non-score board.

Based on the shot change detection and main features extraction, seven kinds of shot are classified: (1) Center Shot, (2) Up Shot, (3) Non-Score Board Shot, (4) First Goal Long shot, (5) Last Goal Long shot, (6) First and Last Goal long shot and (7) Event shot.

To realize highlight detections in soccer games, high-level semantic information embedded in the video is needed. Therefore, three kinds of semantic layers are defined as follows: High-level layer: Goal Scene, Replay Scene and Event Scene. Middle-level layer: Center Shot, Up Shot, Non-Score Board Shot (*NSB* shot), First Goal Long shot (*FGL* shot), Last Goal Long shot (*LGL* shot), First and Last Goal long shot (*FLGL* shot).Low-level layer: Average 16*8MB number, Average Ground MB number, Field line slope, Score board information, GOP number in one shot, etc.

4. SEMANTIC ANALYSIS USING BN

4.1. Training

A training can be categorized into two kinds: the qualitative (structural) training and the quantitative (parameter) training. The qualitative training concerns the network structure of the model and the quantitative training determines the specific conditional probabilities.

(1) The qualitative training: Previous shot change detection and shot classification were prepared for the structure training. One kind of highlight scene is consists of two or three kinds of consecutive shots (shown in Figure 9 (a)). These shot patterns were observed in this step, for example, the shot pattern $2 \rightarrow 3$ (two consecutive shots, the former number is shot type 2, the latter is shot type 3) were observed for the Replay Scene. Each kind of shots has certain main features. For example, the shot type 2 (Up shot) boasts the features: C7 and C0. The shot type 3 (Non-Score Board Shot) is related to the features: C4 and C8.

(2)The quantitative training: In the quantitative training, some dependence between the nodes and the occurrence possibility of each node in the network will be calculated. The training procedure can be divided into two steps as follows:

Step1: In this step, we compute all the conditional probabilities between high-level nodes and middle-level. If the joint appearances of two nodes happen, single appearance of the high-level node should be counted. For example, the conditional probability of Up Shot, given the Replay Scene happen, can be calculated:

$$P(\text{Up Shot} = \text{True} \mid \text{Replay Scene} = \text{True})$$
$$= P(\text{Replay Scene}=\text{True}, \text{Up Shot}=\text{True})/P(\text{Replay Scene} = \text{True}).$$

Step2: In this step, the condition probability of the existing link between the features and shots will be calculated. It is carried for each pair between the middle-level and low-level nodes. If joint appearances of two nodes happen, the single appearance of the middle-level node should be counted. For example, the conditional probability of feature C7, given the Up Shot happen, can be calculated as:

$$P(C7=\text{True} \mid \text{Up Shot} = \text{True})$$
$$= P(\text{Up Shot} = \text{True}, C7 = \text{True})/ P(\text{Up Shot} = \text{True}).$$

In the training step, we have used 16 hours of live-recordings of soccer videos for training. Training video data is used to construct DAGs and compute prior probabilities of each highlight scene BN. Some kinds of BNs for each highlight scene are shown in Figure 9.

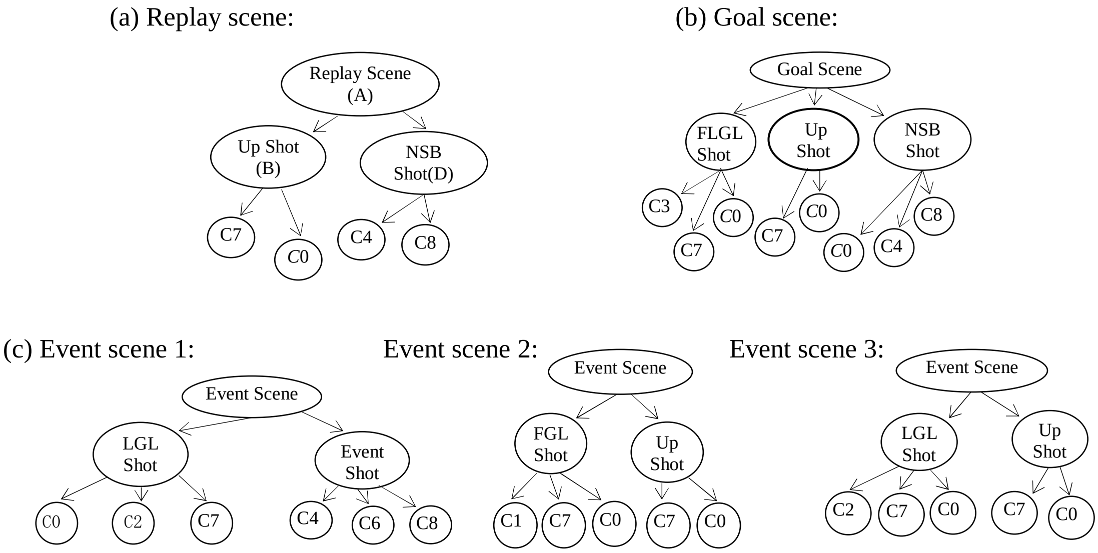

Figure 9. BNs for each highlight scene

4.2. Computing posterior probability

The inference can be performed using various algorithms such as expectation maximization, variational algorithms [11], belief propagation, Markov Chain Monte Carlo, particle filter, etc. In this paper, we have customized the application for soccer video sequences and used Variable Elimination algorithm [11] for inference. We present here one of the simplest inference algorithms for answering these types of queries, which is based on the principle of variable elimination. Our goal here is restricted to computing the probability marginal distributions under the assumption that some evidences are given in advanced.

4.2.1. Factors

Before we discuss the method of variable elimination in our BN, we first need to discuss its central component: a factor.

A *factor f* is a function over a set of variables, mapping each instantiation x of these variables X to a non-negative number, denoted *f*(x) [11]. For example, in Fig.9 (a),

$$f(A)=P(A),$$

$$f(A,B,D)= P(B|A)P(D|A)P(A).$$

Most of the computations we perform on factors will start with factors that represent conditional probabilities and end up with factors that represent marginal probabilities.

4.2.2. Elimination as a basis for inference

The Variable Elimination algorithm provides pseudo code for computing the marginal over some variables Q in a Bayesian network based on the previous elimination method. The algorithm takes as input a Bayesian network N, variables Q, some instantiations e and an elimination order π over remaining variables, here π(1) is the first variable in the order, π(2) is the second variable, and so on. The algorithm iterates over each variable π(i) in the order, identifying all factors f_k that contain variable π(i), multiplying them to yield factor f, summing out variable π(i) from f, and finally replacing factors by factor $\sum_{\pi(i)} f$. When all variables in the order π are eliminated, we end up with a set of factors over variables Q. Multiplying these factors gives the answer to our query, that is the joint marginal Pr(Q, e).The method of variable elimination[11] can be extended to compute joint marginal if we start by zeroing out those rows in the joint probability distribution that are inconsistent with instantiations e.

Table2. Result of detect shot change

Video	CC	CDC	ADC	Recall	Precision
Video1	427	411	445	96.3%	92.4%
Video2	300	294	306	98.0%	96.1%
Video3	676	602	620	89.1%	97.1%
Video4	208	182	206	87.5%	88.3%
Sum	1611	1489	1577	92.4%	94.4%

Table3. Results of Event Scene detection

Video	CS	CDS	ADS	NDS	FDS	Recall	Precision
Video1	89	67	81	22	14	75.2%	82.7%
Video2	57	45	48	12	3	78.9%	93.8%
Video3	120	78	84	42	6	65.0%	92.9%
Video4	42	29	31	13	3	69.0%	93.5%
Sum	308	219	244	89	26	71.1%	89.8%

5. RESULTS AND ANALYSIS

In the training phase, 5 video games (450min) are used to generate our BNs for each kind of highlight scene. In the testing experiments, we have tested 5 hour 20 min video sequences from four soccer programs. The proposed algorithm is evaluated by using 4 MPEG-2 soccer videos. The video resolution is 1440×1080 resolution and played back in 29.97 frames per second. For each detection evaluation,

(1) Shot change detection accuracy

Two metrics are defined to describe the detection accuracy; the recall and precision. The recall is defined to be the ratio of the number of correct detections and missed detections, and the precision is defined to be the ratio of the number of correct detections to both correct detection to both correct detection and false detection. That is, the Recall and the Precision are given by:

$$\text{Precision} = \frac{CDC}{ADC} \times 100\% \qquad \text{Recall} = \frac{CDC}{CC} \times 100\%$$

Here, CDC denotes the number of correct detection, CC denotes the number of existing shot changes, and ADC denotes the number of all detection.

The Table 2 shows that it is suitable to use MB type information to detect shot change, which is benefit for the shot classification and video structure further head, and strongly contribute to our BN construction.

Table4. Result of Goal Scene detection

Video	CS	CDS	ADS	NDS	FDS	Recall	Precision
Video1	4	3	4	1	1	75.0%	75.0%
Video2	2	2	2	0	0	100%	100%
Video3	2	2	3	0	1	100.0%	66.7%
Video4	4	3	3	1	0	75.0%	100.0%
Sum	12	10	12	2	2	83.3%	83.3%

Table5.Results of Replay Scene detection

Video	CS	CDS	ADS	NDS	FDS	Recall	Precision
Video1	32	29	32	3	3	90.6%	90.6%
Video2	38	35	36	3	1	92.1%	97.2%
Video3	34	30	30	4	0	88.2%	100%
Video4	43	39	43	4	4	91.0%	91.0%
Sum	147	133	141	14	8	90.1%	94.3%

(2) Scene detection accuracy

Some other metrics are defined to describe the scene detection accuracy. They are Correct Scene, Correct Detected Scene, All Detected Scene, Not Detected Scene, and False Detected Scene. For simplicity, we denote CS the number of already known scenes, CDS the number of all correct detection, and ADS as the number of all detection, NDS the number of miss detection and FDS the number of false detection. Table 3, 4 and 5 show the result of recall and precision for Event Scene, Goal Scene detection and Replay Scene.

The performances of scene annotation are shown in Table 3, 4 and 5. We observed a high 90.1% recall and 94.3% precision for Replay Scene (shown in Table 5).In Table 3, we observed 71.1% recall and 89.8% precision for Event Scene. For Goal Scenes, we observed average 83.3% and 83.3% recall and precision, respectively. The performance of goal scene is not so high due to the limit training samples of goal scene in the whole training data, and the BN of goal scene should be modified further in our future work.

6. CONCLUSION

In this paper, we have presented a highlight scene detection system based on structured video and Bayesian networks. The proposed framework analyzes the low-level features mainly extracted from MPEG-2 codec video directly and high-level semantic concepts. Our results demonstrate that the video structured scheme, especially the shot change detection and detail shots classifications we proposed, is very helpful and meaningful to BNs construction and semantic analysis. Meanwhile, by extracting the main features embedded in MPEG-2 codec without complex image processing, the computing time is decreased, so that our system has the capability to analysis high-definition (1440×1080 resolution) soccer videos in real time.

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