GENERIC PLAY-BREAK EVENT DETECTION FOR SUMMARIZATION AND HIERARCHICAL SPORTS VIDEO ANALYSIS

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ABSTRACT

This paper proposes a single generic real-time (or near real-time) play-break event detection algorithm for multiple sports, which include football, tennis, basketball, and soccer. The proposed algorithm only uses shot-based generic cinematic features, such as shot type and shot length. Detected play-break events are employed for two purposes: 1) All plays in certain sports, such as football and tennis, are presented as summaries, and 2) Play-break events, as part of a hierarchical event detection scheme, determine the segments-of-interest for the other event detection algorithms. An example of such event detection algorithms is given for soccer goal events, where the proposed soccer goal detection algorithm exploits the common cinematic techniques that are employed during the breaks that follow the goal plays. We demonstrate the generic nature of the proposed play-break detection algorithm over football, tennis, basketball video and the effectiveness of the proposed soccer goal detection algorithm over a large data set.

1. INTRODUCTION

Sports video appeals to large audiences and has been commonly employed to promote new technological advances, including 3-G wireless standard (e.g. NTT DoCoMo in Japan), HDTV, and some web services. Automatic and real-time sports video summarization is desirable for many applications, e.g., real-time sports video delivery over low-bandwidth channels (wireless and some of the Internet) and automatic recording of personalized game summaries by Personal Video Recorders (PVRs), such as TiVo and ReplayTV. Most of these applications inherently require real-time processing and/or low computational power. In [1], we classified video features as cinematic and object-based features. Cinematic features are derived from video structure, such as shot and scene features, and result from film conventions and rules that are commonly applied by broadcasting crews. The resulting visual features thereof are usually applicable to various genres, including multiple sports, film [2] and so on. In addition to their generic nature, cinematic features are also computationally more resource-friendly. In contrast, although object-based features, such as player trajectories and their motion characteristics, enable higher-level video analysis, they are usually domain(sports type)-specific and their extraction is computationally more demanding and may not be robust.

In this paper, we use generic cinematic features, such as shot length, shot type, and slow-motion replays, to detect play-break events in multiple sports, which include basketball, football, tennis, and soccer, with a single algorithm. Then, we demonstrate the applications of play-break detection to summarization of sporting events and to hierarchical sports video analysis, which involves developing event detection algorithms that exploit detected plays and breaks. An example of such event detection algorithms is given for soccer goal events. The existing sports video analysis works usually neglect shot-based cinematic features; hence, the proposed algorithms and the use of shot length in this paper are novel contributions in the sports video processing domain.

In the next section, we define shot types in sports video. Then, in Sec. 3, a novel and generic play-break detection algorithm for sports video is described. In Sec. 4, soccer goal event detection algorithm is presented. Finally, we demonstrate the generic nature of the proposed play-break detection algorithm over basketball, football, and tennis video, and effectiveness of the proposed soccer goal detection algorithm over a large data set.

2. SHOT TYPE CLASSIFICATION

Shot boundary detection is usually the first preprocessing step in video processing. In [1], we proposed a robust shot boundary detector for sports video. After detecting shot boundaries, we classify each shot into three classes because cinematographers generally use long, medium, and close shots to capture a scene [3]. The definitions and semantics of these shot classes are usually domain-dependent; hence, in [4], we defined these three classes for sports video as:

- **Long shot**: A long shot displays the global view of the field as shown in Fig. 1 (a) and (b).
- **Medium shot**: A medium shot, where a whole human body is usually visible, is a zoomed-in view of a specific part of the field as in Fig. 1 (c) and (d).
- **Close-up or out-of-field shot**: A close-up shot usually shows the above-waist view of a player (Fig. 1 (e)). The audience, coach, and other shots are denoted as out-of-field shots (Fig. 1 (f)). In the remainder of this paper, we will use the term close-up shots (or close-ups) to refer to both close-ups and out-of-field shots.

3. PLAY-BREAK EVENT DETECTION

Sports video is composed of play events, which refer to the time segments when the ball is in action, and break events, which refer
to the stoppage times in the game. Break events may be frequent and may take a considerable amount of broadcasting time in some sports, such as football, tennis, and baseball. Therefore, detection of play and break events makes it possible to generate concise lossless summaries consisting of all play events in a specific game. Furthermore, detecting play and break events enables a hierarchical semantic analysis. For example, all play events may be further processed to detect certain events.

Play-break detection algorithm uses shot type and shot length features. As explained in Sec. 2, sports video is composed of long, medium, and close-up shots. Among these shots, long shots usually correspond to play events, while close-up shots indicate breaks in the game as shown in Figs. 2 and 3. However, it is not uncommon for the broadcasters to use long shots during a break. Therefore, in addition to shot type, we also use shot length to locate play events. For that purpose, the system computes the minimum length of a long (view) shot, $L_{\text{min}}$, that refers to a play event from the training videos. Then, as shown in Fig. 4, long shot play events are localized by comparing the length of each long shot against $L_{\text{min}}$, and labeling each long shot having length longer than $L_{\text{min}}$ as play.

Play events are usually captured as long shots, but during plays, or immediately after interesting actions on the field, medium shots or player close-ups may be used to highlight certain objects for a short time. These are essentially play events and should be labeled as plays. In order to detect such play events, we use another parameter, $T_B$, which can be defined as the maximum allowable time between two long shot play events. If the interval between two long shot play events is shorter than $T_B$ sec, the corresponding segment is labeled as play. Otherwise, it is described as break. Unlike [7], which uses football field structure for play event localization, and [8], which exhaustively models shot type transitions in soccer games, the proposed play-break event detection algorithm is generic in that it uses domain information through only $L_{\text{min}}$ and $T_B$ that can be passed as parameters to the same algorithm for different type of sports. In the proposed algorithm, the value of $T_B$ determines the actual compression rate for the generated summary; as $T_B$ increases, the summary length increases since some break events are also included to the summaries. In Sec. 5.1, we elaborate on its effect in the compression rate and in the play-break event detection accuracy.

4. SOCCER GOAL EVENT DETECTION

A goal is scored when the whole of the ball passes over the goal line, between the goal posts and under the crossbar [5]. Unfortu-
nately, it is difficult to verify these conditions automatically and reliably by video processing algorithms. However, occurrence of a goal is generally followed by a special pattern of cinematic features, which is what we exploit in our proposed goal detection algorithm. Because soccer games stop after goal events, a goal event leads to a break, when broadcasting crews convey the emotions on the field to the TV audience and show one or more replay(s) for a better visual experience. The emotions are captured by one or more close-up views of the actors of the goal event, such as the scorer and the goalie, and by shots of the audience celebrating the goal. For a better visual experience, several slow-motion replays of the goal event from different camera positions are shown. Then, the restart of the game is captured as a long shot. Between the long shot resulting in the goal event and the long shot that shows the restart of the game, we define a cinematic template that should satisfy the following requirements:

- Duration of the break : A break due to a goal lasts no less than 30 and no more than 120 seconds.
- The occurrence of at least one close-up/out-of-field shot : This shot may either be a close-up of a player or out-of-field view of the audience.
- The existence of at least one slow-motion replay shot : The play that leads to a goal is always replayed one or more times. Slow-motion replays are detected by the algorithm proposed in [6].
- The relative position of the replay shot : The replay shots follow the close-up/out-of-field shots.

In Fig. 5, the occurrence of the cinematic template for the first goal of the Spain-Sweden soccer video in the MPEG-7 data set is demonstrated. The search for goal event templates starts by detecting slow-motion replay shots. For every detected slow-motion replay shot, play events that define the start and the end of the corresponding break are located by finding two long shots (one before and one after the replay shot) whose lengths must be larger than $L_{\text{min}}$, which is defined in Sec. 3. Finally, the template features, defined below, are verified to detect goals. The proposed cinematic template models goal events very well, and the proposed algorithm runs in real-time with a high recall rate.

![Fig. 5. The broadcast of the first goal in Spain1: (a) long shot of the actual goal play, (b-e) break event due to the goal ((a) player close-up, (c) audience, (d) the first replay, (e) the third replay), and (f) long view of the start of the new play](image)

<table>
<thead>
<tr>
<th>$T_B$ (sec)</th>
<th>SpainB</th>
<th>NCAAB</th>
<th>KoreaB</th>
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<tbody>
<tr>
<td>5</td>
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<td>0.92, 0.08</td>
<td>0.81, 0.0</td>
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<tr>
<td>10</td>
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<td>1.0, 0.39</td>
<td>1.0, 0.18</td>
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<tr>
<td>30</td>
<td>1.0, 0.25</td>
<td>1.0, 0.39</td>
<td>1.0, 0.18</td>
</tr>
</tbody>
</table>

Table 1. Performance of the proposed play-break event detection algorithm for basketball video (D: play event detection rate, FA: play event false alarm rate)

5. RESULTS

5.1. Play-Break Event Detection

Video clips of three different basketball games, a football game, and a tennis game constitute the experimental setup for play-break event detection. Among basketball sequences, which, together, consist of 35 minutes of MPEG-1 video, one sequence was selected to determine the typical value of long play shot length for basketball games, $L_{\text{min}}$, which is computed to be 7 sec when it is defined as the minimum long play shot length in the ground truth, and the remaining sequences were employed for play-break event detection. The test sequences correspond to basketball and football games from NCAA tournament, and basketball games from Korean and Spanish leagues, the last two of which can also be found in the MPEG-7 experiment set. In addition to variations in the employed cinematography, the physical structures of the basketball courts in the test sequences are also different from each other, which aggravates shot type classification problem. Courts in the NCAA and Korea sequences do not have painted regions, while the court of the Spanish league game has red-colored painted regions under each basket and in the center circle. For football, shot type classes were interactively determined. Automatic shot classification algorithm for tennis video uses only dominant color pixel ratio in a frame. For basketball, because shot type classification algorithm in [9] has been adjusted to favor long shots over medium shots, some medium shots were classified as long shots. However, the algorithm also requires each long shot to satisfy a shot length constraint, $L_{\text{min}}$. Therefore, in our experiments, misclassification of medium shots as long shots did not cause any false alarms for play-break event detection.

Table 1 shows detection (D) and false alarm rate (FA) in basketball sequences for various $T_B$ values. In the experiment, the ground truth play-break event labels were assigned by a human operator. These ground truth play-break segments correspond to 30.9, 22.8, and 18.9% compression rates for SpainB, NCAAB, and KoreaB sequences, respectively. Table 1 shows that the optimal $T_B$ value is dependent on a particular sequence, i.e. game, and a particular broadcaster. For example, in order to capture all plays, $T_B$ should be 30 sec for SpainB sequence, 20 sec for the NCAAB and KoreaB sequences. In spite of these variations, it is still possible to conclude that play event summaries generated by $T_B$ values at the lower half of 10-20 sec interval consist of 92-95% of all play events with a very low false alarm rate, while the upper half of the same interval results in the summaries of almost all, 98-100%, play events with some false positives.
For football video, we used the same $L_{\text{min}}$ value (7 sec.) as basketball since the experimental set consists of only one football video, which had to be in the test set. We fixed $T_{B}$ at 5 sec since, unlike basketball, plays in football games are shorter; hence they are usually shown in a single shot. With these parameters, the same play-break event detection algorithm detected all play events ($D = 1.0$) in the football clip. One break shot was labeled as a play, making $F.A = 0.02$. The resulting compression rate with these values is 68%, which, due to the characteristics of football games, is more than twice the maximum compression rate of basketball video.

We processed 7 minutes of the tennis game in our data set. Shot classification and play-break detection in tennis video is considerably easier than those for basketball and football. The reason is that medium shots in tennis are not used as often as they are in basketball and football. Furthermore, during plays, the camera usually stays stationary and captures the scene from the same view. Therefore, shot classification was performed accurately which brought about ideal recall-precision values at a fixed $T_{B}$ of 5 sec. The summary consisting of all tennis play events consisted of only 32.5% of the whole segment, which resembles football.

5.2. Goal Event Detection

Goals are detected in 15 MPEG-1 soccer test sequences, consisting of more than 13 hours of soccer video. Each sequence, in full length, is processed to locate shot boundaries, shot types, and replays. When a slow-motion replay shot is found, cinematic template features are verified against the conditions in Sec. 4. The proposed goal event detection algorithm runs in real-time, and, on the average, achieves a 90.0% recall (27 goals are detected out of the total 30) and 45.8% precision rates (32 false alarms). We believe that three misses are more important than false positives, since the user can always fast-forward false positives, which also do have semantic importance due to the slow-motion replays. Two of the misses stem from the inaccuracies in the extracted shot-based features, and one miss, where the slow-motion replay shot is broadcast minutes after the goal, is due to the deviation from the goal model. The false alarm rate is directly related to the frequency of the breaks in the game. The frequent breaks due to fouls, throw-ins, offsides, etc. with one or more slow-motion shots may generate cinematic templates similar to that of a goal. The inaccuracies in shot boundaries, shot types, and replay labels also contribute to the false alarm rate. We are currently investigating the use of multimodal information, such as audio, to achieve a high precision rate without sacrificing the current recall rate.

6. CONCLUSION

We presented novel high-level event detection algorithms for goals in soccer and play-break events in various sports by using only cinematic features. We demonstrated the robustness of the proposed algorithms to the variations in cinematic styles of various broadcasters around the world. We believe high-level video processing using cinematography is an optimal trade-off between speedy and accurate processing. We are currently investigating the employment of various other cinematic features to sports video analysis.

7. REFERENCES