

ENHANCED SHOT CHANGE DETECTION USING MOTION FEATURES FOR SOCCER VIDEO ANALYSIS

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ABSTRACT

An enhanced shot change detection algorithm for soccer video analysis is proposed in this paper. Features extracted from reliable motion vectors (MVs) are used to enhance the accuracy and efficiency of color-based method. In order to eliminate unreliable MVs, a MV filtration scheme is designed based on the principle of block-based motion search. Then two features, named as *Proportion of Reliable MVs* and *Centrality of Reliable MVs* respectively, are extracted from the filtration results in each frame. The experiments on 180 minutes' soccer video demonstrate that our algorithm achieved a considerable improvement over the widely-adopted color-based method.[†]

1. INTRODUCTION

Semantic analysis for sports video has been widely studied recent years due to its tremendous commercial potentials. Video shot change detection divides a video sequence into several separate shots, and provides the basis for high-level semantic analysis, like highlight detection. Therefore, an accurate and efficient shot change detection scheme is very important for semantic analysis of sports video.

There are a lot of previous works dealing with shot change detection [1]. The basic idea is to calculate an inter-frame difference according to some features extracted from each frame and determine whether a shot change occurs or not [2]. With respect to soccer video, color-based methods are widely used which usually extract two color features to segment the video sequence [3]: 1) Histogram, which is a global characteristic insensitive to slow motion; 2) Dominant color proportion, which is a unique characteristic of sports video. However, neither histogram nor dominant color proportion is effective in the following two situations which happen in soccer video frequently:

- 1) The frames before and after an abrupt change between a *long shot* and a *medium shot* have similar histograms and nearly the same dominant color proportions, which results in a miss detection (see Fig. 1).

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(a) the last frame of a *long* (b) the first frame of a *medium shot*.

Figure 1. Illustration of a missed shot change.



(a) a typical gradual shot change: graphics wipe



(b) a typical gradual shot change: dissolve



(c) a false detection: fast camera pan

Figure 2. Three situations difficult to distinguish in color-based method.

- 2) During a fast camera pan, the visual content changes as fast as in a gradual shot change, which results in a false detection. In Fig. 2, (a) and (b) are two typical gradual shot changes, (c) is a fast camera pan during which the background changes rapidly.

Motion information provides an alternative approach to solve the above two problems. Akutsu et al. [4] construct one motion-compensated image and compute the color difference between current frame and this constructed image. Similar to color-based method, this method cannot correctly segment the video into shots in the two cases mentioned above. In [5], temporal discontinuity in optical flow is used to detect shot changes. This algorithm is totally different from color-based method, but it is only evaluated by short TV news and series including only about 100 shot changes, and the computational complexity is not mentioned.

To enhance the performance of color-based shot change detection of soccer video, we propose an algorithm by

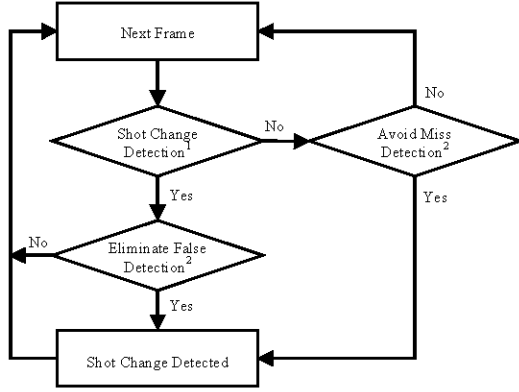


Figure 3. Flowchart of the proposed scheme.
(1: use color-based features. 2: use motion-based features)

adding motion features. Firstly, we design a MV filtration scheme based on the principle of motion search to determine the reliability of a MV. Then two features, named as *Proportion of Reliable MVs* and *Centrality of Reliable MVs*, are extracted based on the reliability of the MVs. Finally, these two motion-based features are used to detect the missed shot changes and eliminate the false detections. Experiments on a large data set are carried out to justify the effectiveness and robustness of the proposed algorithm.

2. FEATURE EXTRACTION

Fig. 3 illustrates the flowchart of our shot change detection scheme. First of all, color-based features are used to detect a possible shot change, but the results may not be accurate enough due to the problems discussed in Sec.1. Therefore, motion-based features are then used to avoid miss detections and eliminate false detections.

2.1. Color-based Features

For each frame at time t , two color-based features F_H and F_C are extracted, which represent the differences of 3-D histogram (H) and dominant color proportion (C) between two frames respectively. The dominant color is modeled in the HSV color space as in [3]. That is, F_H and F_C can be obtained as:

$$F_H(t, s) = \sum_{i=1}^{N_{bin}} |H(t, i) - H(t-s, i)| \left/ \left[2 \sum_{i=1}^{N_{bin}} H(t, i) \right] \right. \quad (1)$$

$$F_C(t, s) = |C(t) - C(t-s)| \quad (2)$$

Where N_{bin} is the number of bins in the histogram, s is the interval between two frames.

Considering the interleave and compression effects in most broadcast videos, the shot changes with an interval of less than 2 frames are defined as abrupt shot changes (also called cuts). Otherwise, they are regarded as gradual ones.

Therefore, for abrupt shot change, $[F_H(t, 2), F_C(t, 2)]$ is directly compared with predefined thresholds to arrive at the decision of shot cut. For gradual shot change, we adopt an optimal detector by modeling a plateau-like pattern of $F_H(t, s)$ inside a time window, as in [8].

2.2. MV Filtration Scheme

Conventionally, MVs are calculated by minimizing the residual between current and previous frames. However, these obtained MVs are not guaranteed to represent the true motion of the corresponding blocks, especially in sports video. For instance, the cases of rapid changing background, large low-textured areas and image blur caused by camera motion would make the MVs arbitrary and unreliable. Therefore, a MV filtration scheme is needed to eliminate such unreliable MVs.

From the perspective of block-matching, we assume that a block which includes a reliable MV should have following properties during the motion search:

- 1) The minimal residual R_{min} that corresponds to the resultant $MV = (X_{MV}, Y_{MV})$ should be small, the smaller the better;
- 2) The residuals between this block and other neighboring candidate blocks in previous frame should be much larger than R_{min} , the larger the better.

So we can decide the reliability of one MV according to its calculated block-matching residuals during the motion search. *Diamond Search* [7] is adopted as fast motion search algorithm and *Sum of Squared Difference* (SSD) is taken as the metric to measure the block difference. After motion search for each block, we obtain 13 R_{SSD} values, among which the minimum is R_{min} . Regarding R_{SSD} as a function of the candidate vector (X, Y) , these values can be fitted into both of the following quadratic curves:

$$R_{SSD} = C_X X_{\Delta}^2 + C_Y Y_{\Delta}^2 + R_{min}, \text{ where } X_{\Delta} = X - X_{MV}, Y_{\Delta} = Y - Y_{MV} \quad (3)$$

$$R_{SSD} = C'_X X_{\Delta}'^2 + C'_Y Y_{\Delta}'^2 + R_{min}, \text{ where } X_{\Delta}' = (X_{\Delta} + Y_{\Delta})/\sqrt{2}, Y_{\Delta}' = (Y_{\Delta} - X_{\Delta})/\sqrt{2}$$

The coefficients of quadratics are computed by curve fitting using *Least Squares Method*. The quadratics in (3) represent two typical elliptical axis directions, which are 45 degrees apart; and the one with smaller square fitting error will be chosen for MV reliability analysis. Analyzing equation (3), it is obvious that R_{min} reflects aforementioned property 1) of reliable MVs, and either (C_X, C_Y) or (C'_X, C'_Y) jointly reflect aforementioned property 2) in different directions. We define the coefficient C as follows, so that the reliability of a MV can be judged by C and R_{min} .

$$C = \begin{cases} \sqrt{C_X C_Y}, & \text{if } E_F < E'_F \\ \sqrt{C'_X C'_Y}, & \text{otherwise} \end{cases} \quad (4)$$

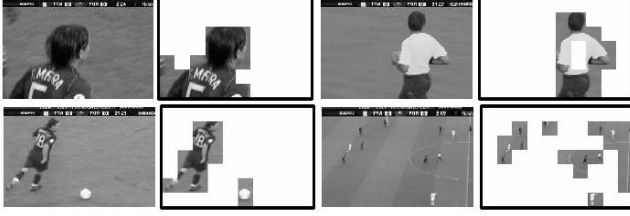


Figure 4. Results of proposed MV filtration scheme. Blocks with unreliable MVs are colored white in the right columns.

where the fitting square errors are defined as:

$$\begin{cases} E_F = \sum_{13 \text{ positions}} (R_{SSD} - C_X X_{\Delta}^2 - C_Y Y_{\Delta}^2 - R_{\min})^2 \\ E'_F = \sum_{13 \text{ positions}} (R_{SSD} - C'_X X'^2_{\Delta} - C'_Y Y'^2_{\Delta} - R_{\min})^2 \end{cases} \quad (5)$$

In order to filter the obtained MVs, each of them is classified as reliable or unreliable according to C and R_{\min} . Such a MV classifier is obtained through supervised offline training, in which more than 1000 MVs are randomly selected from the training video sequences and manually labeled as reliable or not. A MV should be classified as unreliable if R_{\min} is too large or C is too small; otherwise, the two sample clusters (reliable and unreliable), as has been found, can be well partitioned by a linear decision plane. The consequent classifier is determined as follows.

$$\begin{cases} \text{unreliable,} & \text{if } (C < T_C) \vee (R_{\min} > T_R) \vee (R_{\min} > \alpha \cdot C + \beta) \\ \text{reliable,} & \text{otherwise} \end{cases} \quad (6)$$

Fig. 5 gives some illustrative results after MV filtration in the test video sequences. It can be seen that our scheme can effectively judge the reliability of MVs.

2.3. Motion-based Features

Most existing approaches extract features from the magnitude and direction of the MVs in a frame [4][6]. These features can reflect the characteristics of camera operation and object movements, with the prerequisite that all the MVs are reliable. We argue that the reliability of MVs is much more important than the magnitude and direction of MVs in shot change detection.

First of all, we extract a motion-based feature to solve problem 1) mentioned in Sec. 1. Analyzing the missed shot changes where both histogram and dominant color proportion change little, we observe that few reliable MVs exist on the shot boundary in this situation. So, we extract the *Proportion of Reliable MVs* (F_P) for each frame:

$$F_P(t) = \sum_{i=1}^{N_H} \sum_{j=1}^{N_V} M_{MV}(t, i, j) / (N_H \times N_V) \quad (7)$$

Where (i, j) is the coordinate of a block. N_H and N_V are the number of blocks in horizontal and vertical directions in a frame. M_{MV} is a $N_H \times N_V$ binary mask matrix of reliable MVs.

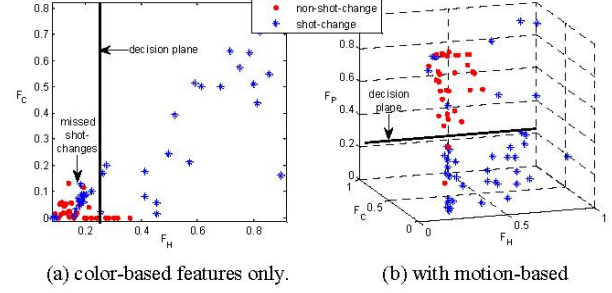


Figure 5. Use F_P to detect missed shot changes.

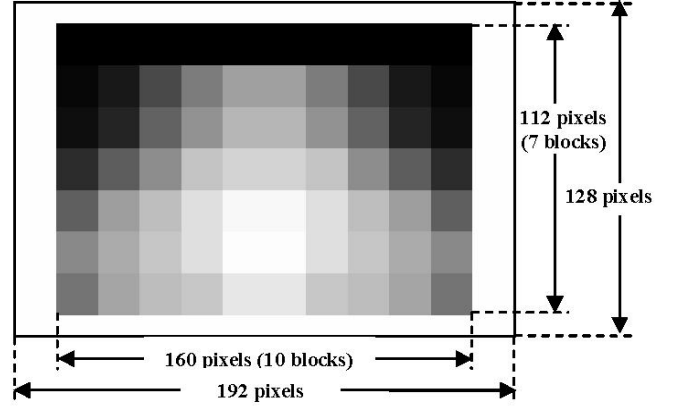


Fig. 6. Illustration of the weight matrix. (the grayscale of blocks represent their reliability probability in fast camera pan clips, white = 1, black = 0.)

Consequently, the missed shot changes can be detected once F_P is less than a predefined threshold which is obtained by training. Fig. 5(a) shows that some shot changes will be missed when only color-based features are used. With the help of motion-based feature F_P , they can be easily detected (see Fig. 5(b)).

Considering problem 2) mentioned in Sec. 1, we find that most false detections are caused by fast camera pan. So, we extract another motion-based feature to discriminate fast camera pans from gradual shot changes. When the camera is panning fast to track a running player with a close-up view, the background usually becomes blurred because it is out of focus and moving fast relative to the camera; while the foreground object remains clear and locates stably in the central region of the frame. As a result, the blocks with reliable MVs are densely distributed in the central region of the frame. In contrast, such blocks, if exist, are arbitrarily distributed during a gradual shot change.

Hence, in order to eliminate false detections caused by fast camera pan, we extract another motion-based feature *Centrality of Reliable MVs* (F_L) as follows:

$$F_L(t) = \sum_{i=1}^{N_H} \sum_{j=1}^{N_V} [W_{MV}(t, i, j) \cdot M_{MV}(t, i, j)] / \sum_{i=1}^{N_H} \sum_{j=1}^{N_V} M_{MV}(t, i, j) \quad (8)$$

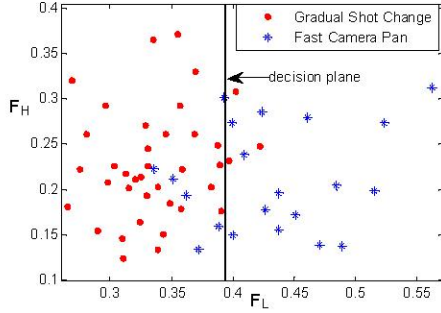


Figure 7. Use F_L to eliminate false detections caused by fast camera pan.

Where W_{MV} is a $N_H \times N_V$ statistical weight matrix for MVs in which each element is a normalized value in $[0, 1]$ representing the possibility of the occurrence of a reliable MV. W_{MV} is obtained beforehand by temporally accumulating the M_{MV} of about 20 fast camera pans (about 1 second long each) collected from the training data set. Fig. 6 demonstrates the W_{MV} in the form of an image, where the intensity is in proportion to the probability. So the frames during a fast camera pan clip are assumed to have larger F_L values than those during a gradual shot change clip.

Once a possible gradual shot change is detected, we will judge it is true or false by averaging the F_L of each frame within this detected shot change and comparing it with a predefined threshold. Fig. 7 shows that fast camera pans and gradual shot changes can be well classified by using F_L .

3. EXPERIMENTAL RESULTS

In order to evaluate our algorithm, several representative soccer videos from World Cup 2006 are selected, including four half-time-long (45 minutes) soccer videos, i.e., 180 minutes in total. One half-time-long match is used as the training sequence, and the other three (including 702 cuts, 141 gradual shot changes) are used to evaluate our method.

Firstly, the frame size is down-sampled to 192×128 so as to reduce motion-estimation computational cost. We consider the motion compensation on the left-most and right-most 16 columns and top and bottom 8 lines unreliable because of camera movements and operations. Thus, motion estimation is operated on the luminance component of the central 10×7 blocks with size of 16×16 (see Fig. 6).

Tab. 1 illustrates the experimental results. We can achieve high precision and recall, 3.3% gain in precision and 4.2% gain in recall over color-based scheme. The adding motion features proposed in our method can bring in considerable improvement to the performance of shot change detection. Moreover, the extra computational cost used for motion-based method is acceptable. When motion-based features are used, the average processing speed reduces from about 42 FPS to about 33 FPS (obtained on a standard PC with P4-1.7G CPU and 1GB RAM), i.e., computational time will approximately increase by 27%.

Table 1. Comparison of shot change detection result

	Correct	Miss	False	Precision	Recall
Color-based features only	760	83	62	92.5%	90.2%
With motion-based features	796	47	35	95.8%	94.4%

4. CONCLUSION

In this paper, we proposed an enhanced video shot change detection algorithm for soccer video analysis using features extracted from filtrated MVs. The proposed MV filtration scheme performs well to determine the reliability of a MV. Obvious improvement on the accuracy of the results proves the effectiveness of our method. Moreover, this method can also be applied to video shot change detection for other sports, such as baseball, tennis and basketball.

5. ACKNOWLEDGMENT

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