A Rapid and Robust Method for Shot Boundary Detection and Classification in Uncompressed MPEG Video Sequences

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Abstract
Shot boundary and classification is the first and most important step for further analysis of video content. Shot transitions include abrupt changes and gradual changes. A rapid and robust method for shot boundary detection and classification in MPEG compressed sequences is proposed in this paper. We firstly only decode I frames partly in video sequences to generate DC images and then calculate the difference values of histogram of these DC images in order to detect roughly the shot boundary. Then, for abrupt change detection, shot boundary is precisely located by movement information of B frames. Shot gradual change is located by difference values of successive N I frames and classified by the alteration of the number of intra coding macroblocks (MBs) in P frames. All features such as the number of MBs in frames are extracted from uncompressed video sequences. Experiments have been done on the standard TRECVid video database and others to reveal the performance of the proposed method.
Keywords: *Shot Boundary Detection, Classification, Abrupt Change, Gradual Change, MBs.*

1. Introduction

In recent years, the massive amount of digital videos has increased rapidly. There is no effective tool used to indexing and retrieving the video information, it comes forth a new research field in the information technology, i.e. Content-Based Video Retrieval (CBVR). Shot boundary detection is the first step in content-based analysis, indexing, and retrieval of video [1-2]. A shot may be defined as a continuous sequence of frames generated by a single non-stop camera operation [3], which is the basic semantic unit of video content information. Shot boundary detection is to detect the transition frames between adjacent shots.

Transition between shots is mainly classified into two types. One is abrupt change (or called cut), and another is gradual change. In an abrupt change, the first frame of next shot is adjacent to the last frame of previous shot, which products a large difference value between the two adjacent frames. Unlike abrupt change, the boundary between adjacent shots is not obvious in a gradual change but is a transition process including some frames. Gradual change is created by artificial edit. According to the edit effects, gradual change can be classified into various types, such as fade-out, fade-in, dissolves, and so on. Fade-out transition denotes that the several frames in the end of shot become diminishing gradually and even become to a black frame. Fade-in is a reverse transition of fade-out. Dissolve transition is a gradual super-fusion of fade-out and fade-in between the consecutive shots.

It is easy to detect the abrupt change between the consecutive shots. However, detecting the gradual change is difficult. Since the gradual transition is a complex process and has many types. Most algorithms mentioned in recent literature are difficult to provide a unified model to detect abrupt change and gradual change. The step of shot boundary detection is to extract features from frames firstly and then calculate the different value of these frames to make a decision whether a shot change occurred or not. Extraction of frames is from compressed video sequence or from uncompressed video sequence. It is time-consuming to uncompress completely the vast video date. Due to above reasons, in this paper, we propose a rapid and robust method using motion information of B frames and P frames in compressed video sequence for shot boundary detection and classification.

The rest of the paper is organized as follows. A brief introduction of previous related woks is presented in Section II. In Section III, we present the proposed shot detection and classification method. Firstly, the *GOPs* including abrupt change and gradual change are detected, and then accurately located the boundary of abrupt in those *GOPs* and classified the gradual change into fade-out, fade-in and dissolve. In addition, we proposed a method to distinguish gradual change from quick motion of object. In Section IV, experimental results and performance evaluation are given. Finally, we give the conclusions of this paper in Section V.

2. Related Work

Many methods for shot boundary detection have been proposed in recent literatures. A shot boundary can be detected by measuring the difference values between the features extracted from adjacent frames. Some studies on extracting the features from uncompressed video sequences, such as color histogram features [4-6], it is necessary to decode the compressed video streams firstly. Hence these methods lack of spatial information. In the same way, edge and texture information [7-11] is also extracted from uncompressed video sequences to be used in shot boundary detection. As a result, the effect of shot boundary detection is influenced by quick motion of object or camera.

Now, a majority of video has deposited into compressed format So more studies on shot boundary detection are processed in compressed video streams from which the features are extracted such as discrete cosine transform coefficients [12, 13], motion vectors [14] and macro-block coding modes [15-17]. These features are extracted from the coded video bit stream. So the process of decode is omitted. The efficiency of algorithm in which feature is extracted from compressed video sequences is much better than those used in uncompressed video sequences.

Many models have been proposed for shot boundary detection [18, 19]. In [20], a model based on eigen conjugation of adjacent frames is proposed for detection of shot boundary and classify the shot type into cut, dissolve, fade-in and fade-out. A unified model based on global and local features is used to detect the boundary of shot in [3]. In these models, several kinds of features are fused in order to improve the accuracy rate of detect the shot boundary. However, the complexity of algorithms increases.

Our work may be marked out as using the features which are extracted completely from uncompressed video stream and these features information indicate the shot boundary and its type. The experimental results show that our method is effective.

3. Shot Boundary Detection and Classification Method

3.1 Rough Detection of Shots Boundary

In MPEG video sequences, only I frame is intra coded frame, and its DC images are obtained by extracting DC coefficient of DCT coefficient in video code stream.

The difference value between two successive DC images of I frame is defined as given below,

$$HD(I_i, I_{i+1}) = \sum_{k=1}^{N} \frac{(H_i(k) - H_{i+1}(k))^2}{(H_i(k) + H_{i+1}(k))^2} \quad (1)$$

Where I_i and I_{i+1} is the ith I frame and the (i+1)th I frame respectively, H_i and H_{i+1} is the histogram of DC images of ith I frame and the (i+1)th I frame respectively.

Using the deference between two successive DC images of I frame, we can detect roughly abrupt change and gradual change. If the deference between two successive DC images of I frame reaches a peak value, then an abrupt change is detected. On the contrary, there is no shot change.

All frames in MPEG video sequences are organized in forms of GOP which begins with an I frame and includes 12 or 15 frames. The rate of video play is 30 frames per second, that is to say, the play time between two successive I frames is 0.5 second. If the two I frames are both in a shot sequence, it is impossible that shot change from A to B and then from B to A in the time of 0.5 second. Therefore, there is only one or zero shot change in a GOP . As a result, if the difference values on N (N>2) successive I frames are detected and all reach to the obvious peak values, the shot change is a gradual change but not N abrupt changes.

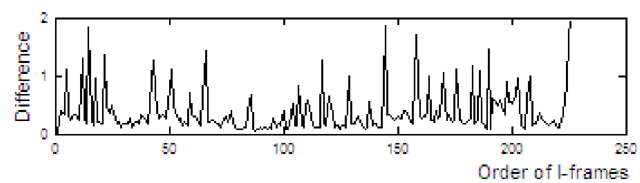


Fig. 1 Difference Values among successive I frames

Fig. 1 shows the difference values between two successive DC images of all I frames in the video BOR08_001.mpg downloaded from TRECVid. From figure 1, it can be seen that difference values between DC images of I frames reach obvious peak values on the *5*th, *12*th, *15*th, *18*th, *22*nd, *43*th, *50*th, *51*st, *59*th, *65*th, *66*th, *85*th, *86*th, *96*th, *100*th, *104*th, *107*th, *110*th, *111*st, *117*th, *128*th, *129*th, *138*th, *144*th, *145*th, *158*th, *159*th, *164*th, *170*th, *176*th, *183*th, *186*th, *190*th, *192*nd, *201*st, *202*nd, *203*th, *207*th and the *208*th I frame, so we can determine that abrupt changes occur in the corresponding $GOPs$ (i.e. $GOP(4)$, $GOP(11)$, $GOP(14)$, $GOP(17)$, $GOP(21)$, $GOP(42)$, $GOP(58)$, $GOP(95)$, $GOP(99)$, $GOP(103)$, $GOP(106)$, $GOP(116)$, $GOP(137)$, $GOP(163)$, $GOP(169)$, $GOP(175)$, $GOP(182)$, $GOP(185)$, $GOP(189)$, $GOP(191)$) and gradual changes appear in those $GOPs$ (i.e. $GOP(50)-GOP(51)$, $GOP(65)-GOP(66)$, $GOP(85)-GOP(86)$, $GOP(110)-GOP(111)$, $GOP(128)-GOP(129)$, $GOP(144)-GOP(145)$, $GOP(158)-GOP(159)$, $GOP(201)-GOP(203)$, $GOP(207)-GOP(208)$, $GOP(224)-GOP(225)$ in which difference values between successive I frames all reach the peak value.

3.2 Accurate Location of Abrupt Change

As mentioned earlier, if the difference value between DC image of the *n*th I frame which is the first I frame in $GOP(n)$ and the *(n+1)*th I frame which is the first I frame in $GOP(n+1)$

reach a peak value, there is an abrupt change in $GOP(n)$. There are still 14 P frames and B frames in $GOP(n)$, we must accurately detect the exact frame on which abrupt change occurs. In MPEG video sequence, only forward predictive-coded MBs are in a P frame, but a B frame includes both forward predictive-coded MBs and backward predictive-coded MBs. Therefore the motion features of MBs in a B frame are used to accurately detecting the location of shot abrupt changes.

Let N_f denote the number of forward predictive-coded MBs, N_{fb} the number of bidirectional predictive-coded MBs, N_b the number of backward predictive-coded MBs, and N_t denote the total number of MBs in a frame. The ratio of forward motion in a B frame can be defined as follows.

$$R_f(B) = (N_f + N_{fb}) / N_t \quad (2)$$

The ratio of backward motion in a B frame can similarly be defined as

$$R_b(B) = (N_b + N_{fb}) / N_t \quad (3)$$

There are three types of locations where abrupt change possibly occurs in a $GOP(n)$.

(1) Abrupt change occurs before the two successive B frames, it indicates that a large number of MBs in the two successive B frames are coded with backward compensation. The I or P frame before the two successive B frames is the last frame of the previous shot and the first B frame of the two successive B frames is the first frame of the next shot.

(2) Abrupt change occurs between the previous B frame and next B frame. Thus, a large amount MBs in previous B frame are coded with forward compensation and large amount MBs in next B frame are coded with backward compensation. Hence, the previous B frame is the last frame of the previous shot and the next B frame is the first frame of the next shot.

(3) Abrupt change occurs after the two successive B frames, it indicates that a large number of MBs in the two successive B frames are coded with forward compensation. Thus, the second B frame of the two successive B frames is the last frame of the previous shot and the I or P frame after the two successive B frames is the first frame of the next shot.

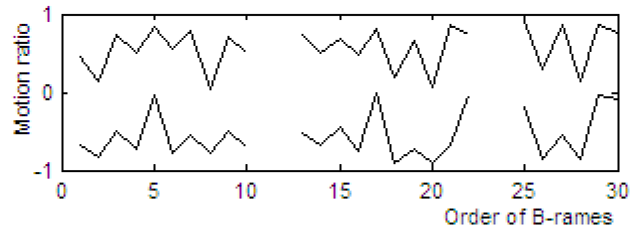


Fig. 2 Macroblock ratio in B frames.

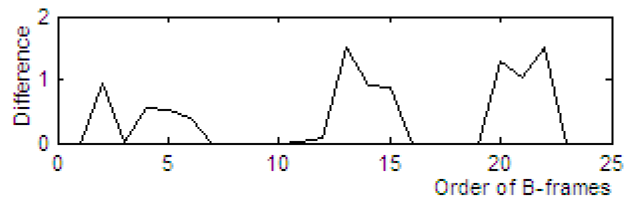


Fig. 3 Difference Values of MB ratio in successive two B frames

Fig. 2 shows the ratio of MBs of B frames in $GOP(11)$, $GOP(14)$ and $GOP(169)$ respectively which includes an abrupt change in the video BOR08_001.mpg. The upper curve is the ratio of forward predictive-coded MBs of B frames, and the lower curve is the relative backward predictive-coded MBs of B frames. In order to detect the exact frame on which abrupt change occurs, we calculate the difference value of forward and backward motion ratio in two successive B frames in every GOP. It can be seen in Fig. 3. In $GOP(11)$, the maximal difference value is on the first two B frames and large number of backward predictive-coded MBs are in these two B frames, as the first case mentioned before, the abrupt change occurs before these two B frames. In $GOP(14)$, the maximal difference value is on the third pair of B frames in which almost all MBs in the first B frame are forward predictive-coded and the large number of backward predictive-coded is in the second B frame. Therefore, as the second case mentioned before, the abrupt change occurs between these two successive B frames. In $GOP(169)$, the maximal difference value is on the last two B frames and large number of forward predictive-coded MBs are in these two B frames, as the third case mentioned before, the abrupt change occurs after these two B frames.

3.3 Accurate Detection and Classification of Gradual Transitions

As mentioned earlier, if all the difference values on N (N>2) successive I frames reach to the obvious peak values, a gradual change is detected. Suppose that all difference values from I_m frame which is in $GOP(m)$ to I_{m+N} frame which is in $GOP(m+N)$ reach to obvious peak value, the duration of gradual change exists in $GOP(m)$ to $GOP(m+N)$. Therefore, we need to detect what type of gradual change occurred in $GOP(m)$ to $GOP(m+N)$.

Assume that gradual change is a linear transition. An I frame within the transition may be represented as follows.

$$I_i - frame = a * I_m - frame + b * I_{m+N} - frame \quad (4)$$

Where $0 \le a, b \le 1$, and $a + b = 1$.

In MPEG video, only forward predictive-coded MBs are in a P frame. If there are more differences in a P frame content among $GOP(m)$ to $GOP(m+N)$ with its forward reference frame, then the number of its predictive-coded MBs will decrease, otherwise, the number of intra-coded MBs in P frame will increase. According to this principle, the number curve of intra-coded MBs in P frames is a special pattern which can be classified to following three types.

(1) In case of fade-out, the number of intra-coded MBs in P frame will increase and reach a peak value at the end of fade-out change.

(2) In case of fade-in, the number of intra-coded MBs in P frame will reach a peak value at the beginning of fade-in change and then taper off.

(3) In case of dissolve, the number of intra-coded MBs in P frame is less change and forms a peak area.

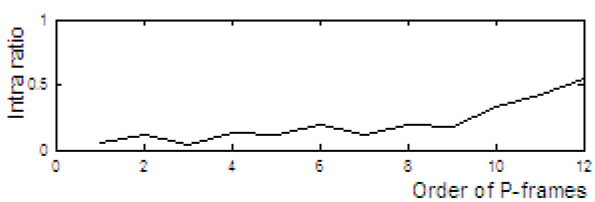
According to the analysis above, we can calculate the number of intra-coded MBs in P frame which is in the range from $GOP(m)$ to $GOP(m+N)$. We calculate the ratio of intra-coded MBs in P frame as follows.

$$R_i(P) = N_i / N_t \quad (5)$$

Where N_i is the number of intra-coded MBs in a P frame, N_t is the total number of MBs in a P frame.

Thus, we can obtain a ratio curve instead of number curve of intra-coded MBs in P frames.

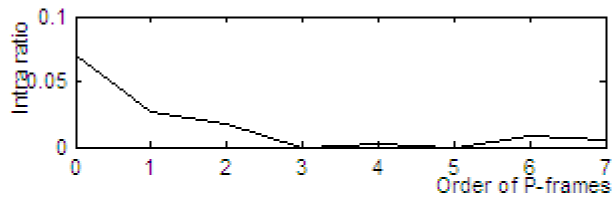
(a) Frames in fade-out.



(b) Ratio of intra-coded MBs of P frames in fade-out

Fig. 4 Frames and ratio of intra-coded MBs in Fade-out

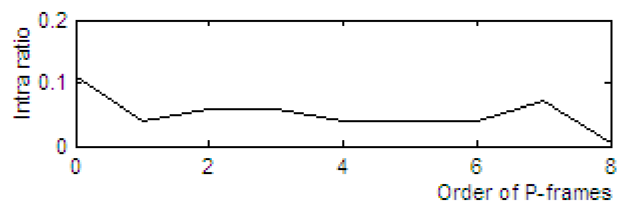
(a) Frames in fade-in



(b) Ratio of intra-coded MBs of P frames in fade-in

Fig. 5 Frames and ratio of intra-coded MBs in Fade-in.

(a) Frames in dissolve.



(b) Ratio of intra-coded MBs of P frames in dissolve

Fig. 6 Frames and ratio of intra-coded MBs in dissolve

Fig. 4(a) shows the change of an image in the process of fade-out transition in $GOP(224)$ and $GOP(225)$ which are in the video BOR08_001.mpg. This image is diminishing overall brightness until to a constant image (usually a black frame) [3]. Fig. 4(b) is the corresponding ratio curve of intra-coded MBs in P frames of this fade-out transition. As the first case mentioned earlier, the ratio of MBs in P frames is increasing gradually and reach a peak value at the end of fade-out change.

Fig. 5(a) shows the change of an image in the process of fade-in transition in $GOP(1)$ and $GOP(2)$ which are in the video narrate.mpg. This is a reverse transition of fade-out. Thus, as the second case mentioned before, the curve of intra-coded

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MBs in P frames of this fade-in transition is decreasing by degrees in Fig. 5(b).

Fig. 6(a) shows the images in the process of dissolve transition in $GOP(50)$ and $GOP(51)$ which are in the video BOR08_001.mpg. These are composite images of the two successive shots. The curve of intra-coded MBs in P frames of this dissolve transition forms a peak area in Fig. 6(b). It accords with the third case mentioned earlier.

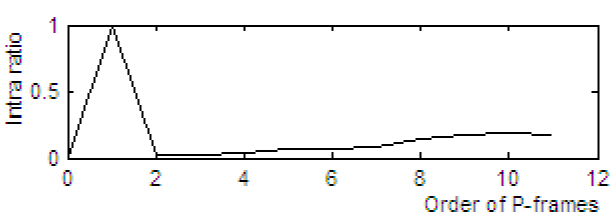
A gradual transition includes all frames in the change process of intra-coded MBs curve (we called peak areas) in P frames. The end of the previous shot is the frame before the peak area and the beginning of the next shot is the frame after the peak area.

3.4 Detection of Quick Motion of Object

Within a shot, there is big change of frame content due to the quick motion of object or camera. Similar to the detection of gradual change, there is also the difference values on N (N>2) successive I frames among the sequence of images which includes the quick motion of object or camera reach to the obvious peak values.

In the process of object or camera quick motion, there is no shot transition. So, predictive-coded B frame or P frame are quite similar to their reference frames. Therefore, the number of intra-coded MBs in P frame is not enough to forms peak area. We can judge the difference value between quick motion of object or camera and gradual change by ratio of intra-coded MBs in P frame which in the frame range of the difference values on N (N>2) successive I frames reach the obvious peak values.

(a) Frames in quick motion of object.



(b) Ratio of intra-coded MBs of P frames in object quick motion

Fig. 7 Frames and Ratio of intra-coded MBs of P frames in quick motion of object

Fig. 7(a) shows the images in the process of quick motion of a photo in $GOP(194)$ 、 $GOP(195)$ and $GOP(196)$ which are in the video story.mpg. The curve of intra-coded MBs in P frames of this process can be seen in Fig. 7(b). It is obvious that there is only one point reach to the peak value and can not form the peak area. Therefore, we conclude that it is a process of quick motion of object but not a gradual transition.

4. Experimental Results and Discussion

The video dataset we used to train our method is collected from TRECVid test database (include BOR08_001.mpg, story.mpg and narrate etc.) downloaded from http://www-nlpir.nist.gov/projects/trecvid/ and other videos include large number of fade-out, fade-in and dissolve. Each of the test video sequences contains about 2000-5000 frames.
Performance evaluation of shot boundary detection is following the TRECVid protocols in terms of Recall, Precision and F-measure [3, 21]. Recall quantifies what proportion of the correct entities is detected, while precision quantifies what proportion of the detected entities are correct. F-measure, a combination of recall and precision, gives the overall performance. They are defined as follows [3].

$$Recall(R) = \frac{Correct}{Correct + Miss} \times 100\% \quad (6)$$

$$Precision(P) = \frac{Correct}{Correct + False} \times 100\% \quad (7)$$

$$F-Measure(F) = \frac{2 \times Precision \times Recall}{Precision + Recall} \times 100\% \quad (8)$$

where $Correct$ is the number of correctly detected shot boundaries, $Miss$ is the number of missing detected shot boundaries, $False$ is the number of false detected shot boundaries.

The detection results of abrupt change using our method in terms of precision, recall and F-measure is shown in Table 1. Table 2 shows the detection results of gradual changes. Detection results of overall changes are shown in Table 3.

Table 1: Detection results of abrupt changes

Video Dataset	***Number of Abrupt Shots***	P (%)	R (%)	F (%)
TRECVid	106	97	96.1	96.5
Others	117	98.2	97.4	97.8

Table 2: Detection results of gradual changes

Video Dataset	***Number of Gradual Shots***		P (%)	R (%)	F (%)
TRECVid	Fade-in	8	90	91.8	90.9
	Fade-out	12			

	Dissolve	34			
Others	Fade-in	33	95.4	92.6	93.9
	Fade-out	27			
	Dissolve	11			

Table 3: Detection results of overall changes

Number of Shots	P (%)	R (%)	F (%)
348	96.1	95.2	95.6

The experimental results indicate that our proposed method can successfully detect almost all abrupt changes, for example, in video BOR08_001.mpg, all abrupt changes are correctly detected. Little false detections for abrupt changes are due to the sudden changes of brightness. Miss detection of shot boundary mainly because of the test video data is encoded in frame structures.

All gradual transitions in TRECVid video and other video dataset are almost correctly detected using the proposed method in section 3.1. , especially, the detection result of fade-out and fade-in is very good.

In order to measure the efficiency of our proposed method, a comparison using the same video dataset is made with the recently reported algorithm in literature [5]. Table 4 shows the comparison result and reveals that the proposed method performs much better than the existing one.

Table 4: Comparison detection result

Adopted Algorithm	P (%)	R (%)	F (%)
Our proposed	96.1	95.2	95.6
Literature [5]	94.6	86.4	90.3

All the detection processes are performed in compressed MPEG video sequences, therefore, the proposed method reaches a very fast operation, about average 1811.7 frames/second on the Windows PC with Pentium Dual E2200 2.20GHz CPU and 2G RAM.

5. Conclusions

In this paper, firstly the rough scan is operated by using the difference value between successive I frames to roughly detect not only the abrupt changes but also the gradual transition in the test video sequences. And then an effective method was provided to accurately detect the first frame and the last frame of shot transition. For abrupt changes, we accurately detect the boundary on which frame according to the ratio of forward and backward predictive-coded MBs in all B frames in a GOP . For gradual changes, we classify into fade-out, fade-in and dissolve types according to the ratio change of intra-coded MBs in P frames. The experimental results show that our proposed methods well realize efficient shot boundary determination, as a result, the precision, recall and F-measure all reached a high value.

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