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Article

A multistage video shot boundary detection approach: robust to motion and illumination effects

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Abstract: In this today's modern era because of increasing digitization and excess growth of multimedia data, video indexing and retrieval tool have become very essential in the field of video retrieval based on content, where video shot boundary detection is regarded as a stage of develop-ment for sudden changes in motion and brightness. A robust multi stage Shot Boundary Detection (SBD) technique is proposed in this present work using Uniform LBP, Canny Edge Detector and Lab Color Differ-ence. The proposed system can identify abrupt shot transition in a video, which are invariant to motion and intensity effects. For extracting fea-tures from each of the frames of a video uniform Local Binary Patterns (LBP) is used. Adaptive threshold δ1 is used to identify possible tran-sition frames. Adaptive threshold δ2 and LAB color difference is used to extract and identify actual transition frames. Motion effects and illu-mination effects are handled in two different phases. At the first stage, effects of brightness and motion effects are reduced by Canny edge de-tection and in the second stage, Lab color difference is used to handle illumination effects. TRECVid 2001 and TRECVid 2007 datasets are used for observation purposes. The proposed method provides good F 1 score compared to other recent shot boundary detection approaches.
Keywords: SBD · LBP · Adaptive threshold · Transition frame

1. Introduction

Due to the advancement in digitization, multimedia data is increasing. Shared multimedia data like audio and video are increasing at an exponential rate over the internet. In the field of online shopping, social networking, health care, bank-ing sector and business sector etc. demand of digital data is increasing. It is a tedious and time-consuming task to organize this massive amount of multi-media data distinctly video data in a methodical and organized manner. For effective video viewing and video browsing it is essential to use some methods or tech-niques for video indexing and retrieval. Video retrieval system based on contents becomes very popular to make video materials accessible. Boundary identifica-tion of video shots is the video segmentation process where video is divided into significant video shots [1]. Based on the transition between consecutive video frames meaningful shots are identified. Transition denotes intermediate bound-aries between successive shots. A transition can be gradual or abrupt transition. Sudden changes in the contents of two consecutive frames leads to an abrupt transition. Minor changes in between consecutive frames lead to a gradual tran-sition [2]. In such a transition period, some of the frames in two consecutive shots complete one intersection. Few challenges like object and camera motion at a time or sudden illumination changes causes high false positives.The novel contribution of this paper is as follows

A multi stage shot boundary detection system is proposed here which accepts multiple stage confirmation to detect shot transition.

Double adaptive threshold verification is proposed to get an effective shot transition detection system.

A robust system is proposed which is invariant to illumination and motion effects.

2. Related Works

Pixel based approach (PBA) is an important transition detection-based approach for fast shot boundary detection. In PBA total pixel count for two consecutive frames are computed. By differentiating the threshold, transition can be pre-dicted [2]. Histogram difference can be regarded as the alternative approach for SBD. Spatial information is not inspected in histogram-based approach to detect abrupt transition. This approach is popular for its motion invariant property and its computational cost [1]. In edge-based approach, minor features of frames are considered. Due to less durability of edge frame feature, edge- based SBD does not give satisfactory result compared to histogram and pixel-based approach. Motion and illumination effects also can be reduced by using edge-based features [3]. Canny edge detector is an important tool to decrease the effects of motion in a video [4]. Block matching algorithm is used to lessen the effects of motion in shot boundary detection method. By comparing the actual frame and the recompense frame the strength of the motion can be calculated using block matching algorithm [5]. Fuzzy logic and genetic algorithm-based approach is ap-plied for shot boundary detection of video contents [6]. The effects of camera and object motion and the effects of illumination can be reduced by using struc-tural similarity and dual tree complex Wevlet Transform. Adaptive threshold gives better result in this case [7]. Illumination effects are removed by DCT and the transformed frame is used to evaluate transition detection using histogram difference [8]. DCT and logarithmic transform-based approach can be used to subdue the effects of illumination as a pre-processing step [9]. While detecting the video shot boundary stationary wavelet transform and cross-correlation co-efficient are used to reduce the effects of sudden illumination like explosion and fire flickers [10]. Time stamp is used to track objects in shot boundary detec-tion. Sequence of frames are identified where a particular object become visible. When the object suddenly fades away from the frame, huge displacement of the object is considered as wipe transition because of random illumination effects in a video [11]. Approaches based on genetic algorithm, fuzzy color histogram, k-nearest neighbour, SVM and convolution Neural Network are some of the ma-chine learning based shot boundary detection technique [12]. Genetic algorithm is used to calculate fuzzy membership function and transition detection iden-tification is done using classification technique [13]. From the research gap it is observed that several research outcomes undergo through illumination and motion effects. In this proposed multistage shot boundary detection system, il-lumination and motion effects are efficiently handled. Slope of objects, structural information and brightness are the frame features of a video that are calculated to predict possible transition phase. LAB color difference is used in the con-firmation phase. TRECVid 2001 and TRECVid 2007 datasets are applied for experiment purpose and it generates more appropriate outcome as compared to other latest techniques.

Background Knowledge

Local Binary Pattern

In the area of computer vision LBP is applied as visual descriptor for clas-sification. In LBP thresholds are applied on the neighbouring pixels with the similar range value of the pixels at the centre. It is a local image descriptor which provides elementary structural information and summarizes local gray scale structure. $3X3$ neighbourhood pixel-based LBP can generate 8 bit integer LBP code. Performance can be improved by combining LBP with Histogram of Oriented Gradients as feature descriptor [14]. While viewing as a circular bit string if at most one 0 to 1 and one 1 to 0 transition is achieved then it is called uniform LBP is shown in equation no 1. LBP Uniform is calculated based on the neighbouring pixel on the circle with radius R. Feature vector is calculated by dividing the frame into m sub-regions as shown in Eq. 1 and 2.

$$(\Sigma_{n-1} S(g_k - g_c) \quad \text{if } U \; \Sigma_{n-1}(g_k - g_c)^2 \le 2^k$$
$$n+1 \quad \text{otherwise } L_{BP}(P_c) = \quad k=0 \qquad k=0 \qquad (1)$$

$$V_{LBP} = [H_1, H_2, H_3 \ldots H_m] \qquad (2)$$

Detection of Canny Edge

Detection of Canny Edge is a widely used edge detection operation that is applied to find a set of edges in images using a multi-step algorithm. Useful structural information is extracted from different vision objects using this technique, which helps to lessen the volume of data to be processed. Canny edge operator produces

a binary edge map E with standard deviation δ and upper and lower threshold values Tl and Th, as shown in Eq. 3.

$$E_B = C_E(I_g, \delta, T_l, T_h) \quad (3)$$

LAB Color Difference

Color difference *CIEDE*2000 originates from the CIELAB color space and is considered perceptually uniform. The *CIEDE*2000 color difference is an im-proved method for computing color differences [?]. It is used in the system to determine the deviation between the video frames. Lab color space is a color model with three dimensions where *CIEDE*2000 color difference is evaluated for a set of CIELab space color values using Eq. 4. Here in the Eq. 4, the dis-similarity in lightness, hue, and chroma of a pair of samples in *CIEDE*2000 is represented by $\Delta L'$, $\Delta H'$, and $\Delta C'$, respectively. To compute the correla-tion between successive video frames in the sequence, CIEDE color difference is used. Here, chrominance components A and B are separated from the lightness component. Chrominance components represent the blue-yellow and green-red differences.

LAB color space efficiently differentiates different color features across the video, and the outcomes after observation manifest that sudden illumination and motion of the objects can be effectively handled by the proposed system.

$$\Delta E_{00} = \Delta E_{00}(L^*_1, a^*_1, b^*_1, L^*_2, a^*_2, b^*_2)$$
$$= \sqrt{\left(\frac{\Delta L'}{K_L S_L}\right)^2 + \left(\frac{\Delta C'}{K_C S_C}\right)^2 + \left(\frac{\Delta H'}{K_H S_H}\right)^2 + R_T \frac{\Delta C'}{K_C S_C} \frac{\Delta H'}{K_H S_H}} \qquad (4)$$

Average perceptible color difference of the consecutive frames provides mean color difference. Mean difference between consecutive frames are shown in Eq.5.

$$D_f(i, i+1) = \frac{1}{L \times B} \sum_{a=1}^{L} \sum_{b=1}^{B} \sqrt{(x_i(a,b) - x_{i+1}(a,b))^2 + (y_i(a,b) - y_{i+1}(a,b))^2 + (z_i(x,y) - z_{i+1}(x,y))^2} \qquad (5)$$

3. Proposed Approach

The proposed methodology is depicted in this module. Features are extracted from the preprocessed frames, and dissimilarity is checked. Thresholds are se-lected for possible abrupt transition and actual abrupt transition. Abrupt transi-tions are detected to have the muti stage shot boundary detection. Diagrammatic presentation of the proposed methodology is shown in Fig. 1.

Preprocessing

Video frames are converted from RGB color space to grayscale images. Size of each of the frames is reduced with the dimensions of 130 by 150. Equalization of the histogram is used for the betterment of the contrast level by modifying the level and distribution of intensity across the pixels of a frame. To make sure the persistence of video sequence Temporal Smoothing is applied to consecutive frames. Temporal Smoothing is also applied to reduce noise in the video sequence.

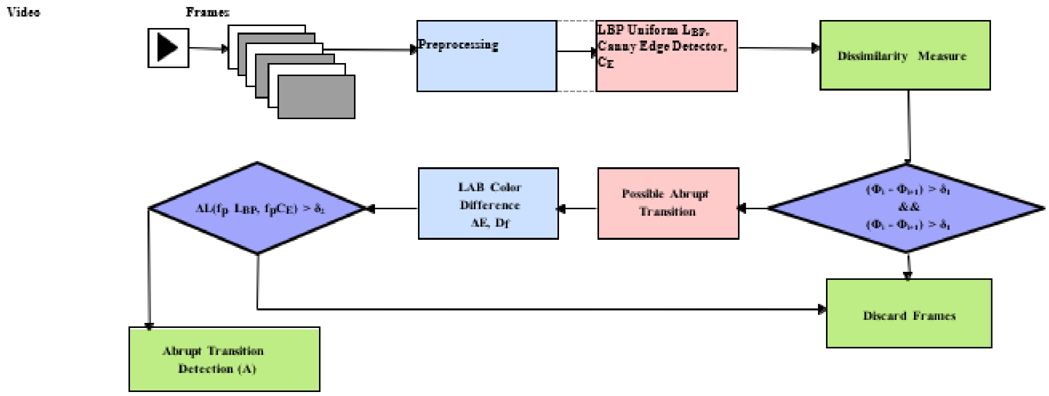

Fig. 1: Proposed multi-stage shot boundary detection

Feature Extraction and Dissimilarity Measure

After the preprocessing stage, features are extracted from each of the video frames. LBP, LAB, optical flow difference, and Canny edge detector are the phases used as feature extraction techniques. Feature extraction techniques iden-tify key features from each of the frames. LBP features are used for texture analysis and help to improve detection performance. LBP is more robust to scal-ing, rotation, and variations of illumination and more sensitive to noise[16]. The identified transition frames are transformed to the Lab color space or CIELAB. CIELAB is a color space that is independent of a device and is planned to be perceptually uniform to human vision. CIELAB separates the lightness (L) com-ponent from the chrominance components ‘a’ and ‘b’. Chrominance components represent green-red color difference and blue-yellow color differences.

Threshold Selection

To classify transition frames and non-transition frames a satisfactory threshold is to be identified. The purpose of using this threshold is to determine an abrupt or cut transition when the difference between two successive frames is beyond that

particular threshold value. By identifying the correct and suitable threshold, the accuracy can be improved while classifying abrupt transitions. As the video has arbitrary data, it is not very convenient to set a distinctive threshold that will work for all videos efficiently. It is essential to set a threshold that can adapt itself according to the structure and data of a video, and this type of threshold is also termed an adaptive threshold. In the proposed approach, an adaptive threshold is identified, which can properly identify transition frames and filter out non-transition frames.

Abrupt Transition Detection

Possible Transition Detection The possible transition phase is the first stage of the proposed approach, where non-transition frames are discarded. This stage begins with feature extraction, and subsequent stages are similarity measure, selection of threshold, and detection of possible transition. Automatic boundary detection of video shots is used to classify abrupt transition. It is considered a multi-stage shot boundary detection approach. The first stage is a possible stage detection approach, and the latter stage is to confirm the transition de-tection. During the first stage of the detection procedure, non-transition frames are abolished. In the later stage actual transition frames are confirmed. This multi-stage detection approach is used to lower false detection. A huge distinc-tiveness between the successive frames is labeled as an abrupt transition in a video. The successive frame features (*post_change*) and (*pre_change*) are com-puted to identify the sudden transition. Eq. 6 and 7 are used to quantify the detection of abrupt transitions where μ stands for mean and σ stands stan-dard deviation. In the possible transition detection phase, LBP and Canny Edge detection features are considered from each of the frames of the video. Similar-ity measure is computed between successive frames of video. If (*pre_change*) is greater than the (*post_change*), then the proposed system experiences an abrupt transition. Constant values of $k1$ and $k2$ are computed as 1.8 and 2.5, respectively. Dissimilarity value is checked for two consecutive *ith* and $(i + 1)th$ frame. If the distinction of the dissimilarity values between Φi and Φi+1 is more than the adaptive threshold $\delta 1$, then the proposed system experiences an abrupt transition. In the proposed approach, the possible transition phase follows the confirmation stage. This phase consists of the extraction of features, the similar-ity measure, the selection of a threshold, and the actual transition detection. If dissimilarity measure values are not more than the adaptive threshold, then the changes as a gradual transition can be considered. If deviation of color score is significantly higher than observed neighboring frame differences determined by adaptive threshold. Eq. 8 is used to quantify the shot detection.

$$\mu(post\_change) \geq k1.\mu(pre\_change) \quad (6) \text{ and}$$
$$\sigma(post\_change) \leq k2.\mu(pre\_change) \quad (7)$$

$$\text{Shot detection} = \begin{matrix} T_{Cut} & \text{if } D(i, i+1) > Th_a(i+1) \\ T_{Gra} & \text{if } D(i+1) > D(i) \\ 0 & \text{no transition} \end{matrix} \quad (8)$$

Actual Possible Transition From the possible transition detection phase, the possible transition frames were selected. In the confirmation phase, actual transition frames are selected from a set of possible transition frames. Due to the pre-processing step, sudden illumination and motion effects in frames are excessively reduced. Then also there are some possibilities to obtain a few more illumination and motion effect frames in the later stages, which were members of possible transition frames. So, the confirmation stage or the post-processing stage is very much essential to determine the correct transition and to lessen false transitions. In the confirmation stage, possible transition frames are selected for confirming in the later stage. It is observed that to detect actual transition

threshold is greater than or equal to $(\mu + \kappa 1 * \sigma)$, as given in the Eq.9 where

$\kappa 1 = 0.35$.

$$Threshold \geq (\mu + \kappa 1 * \sigma) \quad (9)$$

Algorithm: Proposed Abrupt Shot Transition Detection

Algorithm 1 Proposed Abrupt Shot Transition detection

Require: Input video file or, stream V
Ensure: Cut and Gradual T ransition, T otal_Cut

```
procedure VidEO_SHOt_BoUndaRy_DEtEction(V)
    Q ← Read Input Multimedia File(V )
    F1 ← preprocessing(Q1)
    [ΔL, ΔOE, OFD, CED] ← Extracted Features(F);
    while i < Length(Q) do
    |φi - φi+1| >δ1 & |φi−1 - φi| > δ1
    Pi ← Record total possible abrupt frames
    end while
    Else Reject frames;
    for i = 1 to Length(Pabt)-1 do
    if (Threshold ≥ (μ+κ1*σ) then    ▷ Actual Abrupt
        Ai ← Record actual abrupt frames
            T otalcut ← A;
    else
    Reject frame;
    end if
    end for
end procedure
```

4. Results and Discussion

Database

The database plays a prime role in validating the experimental results for the proposed approach. TRECVid2001 and TRECVid2007 are considered here as video databases. To have more dynamic databases, few videos of smaller size and small movie clips are also included. Such videos have more illumination and motion effect-based content. Details of the video datasets TRECVid2001 and TRECVid2007 are presented in Table 1.

Table 1: Video dataset TRECVid 2001 and 2007 applied for observation purpose

Video	Frame number	Cut	Gradual	Total	Sources of video
D2	16586	42	31	73	
D3	12304	39	64	103	
D4	31389	98	55	153	TRECVid 2001
D5	12510	45	26	71	
D6	13648	40	45	85	
BG −3027	49815	126	1	127	
BG −16336	2462	20	-	20	
BG −36136	29426	88	12	100	TRECVid 2007
BG −37309	9639	11	8	19	
BG −37770	15836	8	27	35	

Evaluation Parameters

To analyze the performance of the designed system, evaluation is done using Precision (Pre), Recall(Rec), and F1 score as shown in Eq. 10, 11, and 12. *NC* stands for correctly detected frames, *NM* represents missed frames and *NF* is falsely detected frames.

$$Recall = \frac{N_C}{N_C + N_M} \times 100 \quad (10)$$

$$Precision = \frac{N_C}{N_C + N_F} \times 100 \quad (11)$$

$$F1 = \frac{2 \times REC \times PRE}{REC + PRE} \times 100 \quad (12)$$

The suggested system's algorithm is able to identify potential transitions in the video. The method is made to eliminate the frames that are mostly in charge of changes in illumination and object motion. To obtain better accuracy for each

video in the dataset, adaptive thresholding is used. Adaptive threshold $\delta 1$ and uniform LBP are employed in the potential transition frame detection phase. The confirmation stage makes use of the adaptive threshold $\delta 2$ and the LAB colour difference.

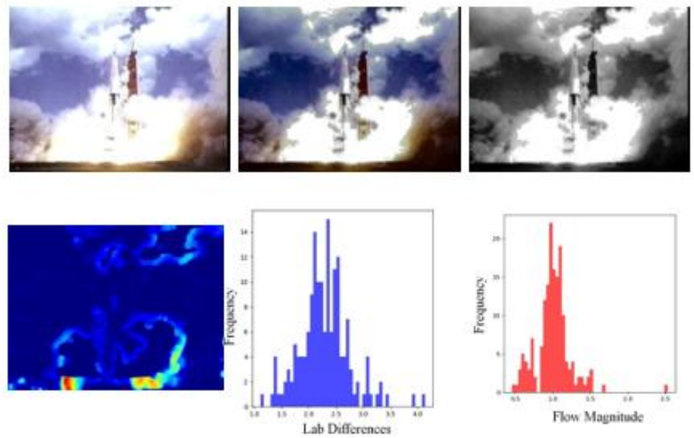

Fig. 2: Feature extraction of video D2 (TRECVid2001 Dataset)

5. Discussion

The algorithm in the proposed system can detect possible transitions exists in the clip of short video. The frames, which are mainly responsible for object motion change and sudden illumination change, are discarded. An adaptive threshold is more beneficial for getting accuracy for all the videos in the dataset. Adaptive threshold generate better results for the proposed approach. In possible transi-tion frame detection phase uniform LBP and adaptive thresholds $\delta 1$ are used. LAB color difference and adaptive threshold $\delta 2$ are used in the confirmation stage. Actual abrupt transition frames are effectively classified in the confirma-tion stage. From the analysis, it is observed that the result of the proposed approach with the confirmation stage performs better. Video D2 and D4 from TRECVid 2001 datasets contain sudden illumination effects for which a set of extracted frame features is depicted in Fig. 2. Generated output depicts frames affeted by sudden illumination from video D2 and D4 of TRECVid 2001, as shown in Fig. 3. Overall system performance for TRECVid 2001 and TRECVid 2007 datasets is shown in Table 2. It is observed that the proposed method is successful in overcoming challenges like object and motion effects, illumination effects, and other challenging effects. Because of the confirmation stage and the effective use of the adaptive threshold the precision value is enhanced and at the same time $F\,1$ score values for all videos of datasets improved drastically.

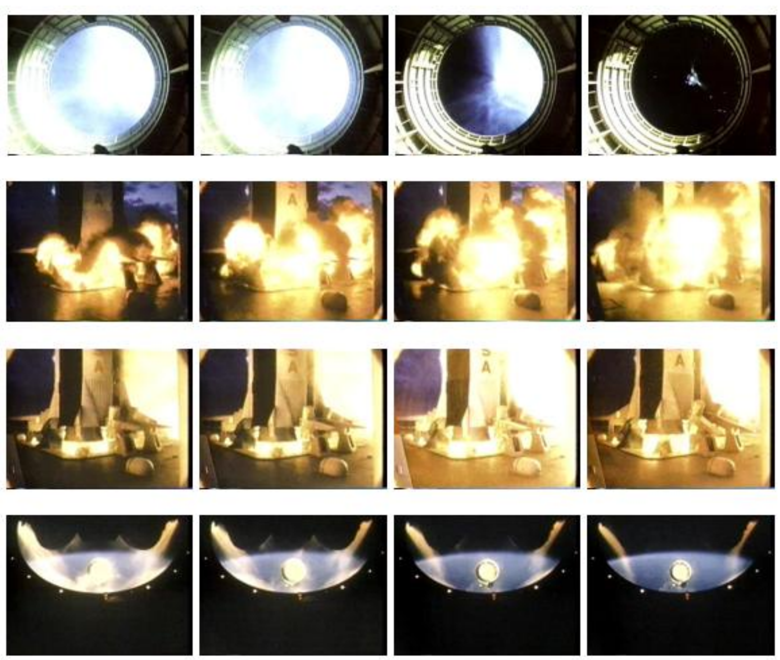

Fig. 3: Handling of sudden illumination changes from video D4 (TRECVid2001 Dataset).

Figure 3 depicts the handling of challenges like sudden changes of uniform and non-uniform illumination. Detected frames from D4 video (TRECVid 2001) is displayed. In the proposed approach, such challenging problems are handled ef-fectively in the confirmation stage.

Performance Comparison

Several state-of-the-art techniques are compared with the proposed technique. The performance of the few state-of-the-art techniques such as ST-CNN [17], PSO-GSA [20], WHT-SBD [21], gradient-oriented feature distance (GOFD) [24], blockbased center-symmetric LBP (BBCSLBP) [27], stationary wavelet trans-form (SWT) [31] and fast framework [33] are compared with the proposed sys-tem. The experimental result of the comparison is manifested here in Table 3. It is observed that the efficiency of the selected videos of TRECVid 2001 (F1 Score) is comparatively better than the other techniques.

Table 2: Overall System performance for TRECVid 2001 and 2007 datasets

Videos	**Cut**			**Gradual**			**Overall**			**Computation Time(Sec.)**
	Rec	**Pre**	**F1**	**Rec**	**Pre**	**F1**	**Rec**	**Pre**	**F1**	
D2	92.8	100	96.3	90.3	100	94.9	91.5	100	95.6	1250
D3	92.3	100	96	96.9	87.3	91.8	94.6	93.6	93.9	732
D4	94.9	100	97.4	98.2	100	99	96.5	100	98.2	2500
D5	100	100	100	96.1	83.3	89.2	98	91.6	94.6	940
D6	95	86.4	90.5	88.9	100	94.1	91.9	93.2	92.3	960
BG_3027	97.6	100	98.8	100	12.5	22.2	98.8	56.2	60.5	3690
BG_16336	100	55.5	71.4	-	-	-	100	55.5	71.4	174
BG_36136	97.7	95.5	96.6	91.7	100	95.7	94.7	97.7	96.1	2350
BG_37309	91	100	95.3	100	72.7	84.2	95.5	86.3	89.7	690
BG_37770	100	80	88.9	85.2	100	92	92.6	90	90.4	1147
Clip1	94.2	100	97	92.9	91.8	92.3	93.5	95.9	94.6	1147
Clip2	100	100	100	92.5	100	96.1	96.2	100	98	1147
Clip3	93.3	100	96.5	100	95	97.4	96.6	97.5	96.9	1147
Clip4	100	94.1	96.9	90	75	81.8	95	84.5	89.3	1147
Clip5	95.6	84.6	89.7	97.2	100	98.5	96.4	92.3	94.1	1147
Clip6	95.6	100	97.7	97.5	90.6	93.9	96.5	95.3	95.8	1147
Clip7	80	100	88.8	90.4	100	94.9	85.2	100	91.8	1147
Clip8	94.4	91.9	93.1	100	92.1	95.8	97.2	92	94.4	1147

Average	**95.2**	**96**	**93.9**	**94.2**	**92.9**	**93.1**	**95**	**90**	**90.4**	**1292.3**

6. Conclusion

A solution with a multistage shot boundary detection technique is provided here to detect gradual as well as abrupt transitions, which is invariant to motion and illumination. Similarity measures are computed for successive frames to detect possible transition frames using an adaptive threshold $\delta 1$. In the confirmation stage Lab color difference is used to validate all possible transition frames using adaptive threshold $\delta 2$. Illumination and motion effects are successfully handled by the proposed system, although a few challenges exist. Future work can be used to detect wipe transition so that the proposed technique can be used as a more effective content-based video analysis and retrieval system.

Declaration

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Disclosure of Interests. The authors declare that they have no conflicts of interest.

Table 3: Determination of performance of the proposed system compared with recent methods.

Methods	**Evaluation Metrics**	**Videos**				**Average**
		***D*2**	***D*3**	***D*4**	***D*6**	
Proposed	R	0.91	0.94	0.96	0.91	0.93
	P	1.00	0.93	1.00	0.93	0.96
	F1	0.95	0.93	0.98	0.92	0.95
[17]	R	0.89	0.92	0.85	0.87	0.88
	P	0.87	1.00	1.00	1.00	0.96
	F1	0.88	0.96	0.92	0.93	0.93
[20]	R	0.97	0.92	1.00	1.00	0.97
	P	0.82	1.00	0.89	1.00	0.92
	F1	0.89	0.96	0.94	1.00	0.94
[21]	R	0.97	0.82	0.88	0.95	0.91
	P	0.85	0.86	0.90	0.97	0.90
	F1	0.91	0.84	0.89	0.96	0.91
[24]	R	0.80	0.82	0.78	0.92	0.83
	P	0.94	1.00	0.96	0.84	0.93

	F1	0.87	0.90	0.86	0.88	0.88
[27]	R	0.78	0.69	0.41	0.85	0.68
	P	0.78	0.72	0.34	0.87	0.68
	F1	0.78	0.71	0.37	0.86	0.68
[31]	R	0.97	0.97	0.93	1.00	0.97
	P	0.06	0.08	0.07	0.08	0.07
	F1	0.12	0.16	0.13	0.16	0.14
[33]	R	0.57	0.46	0.75	0.89	0.67
	P	1.00	1.00	0.98	1.00	0.99
	F1	0.72	0.63	0.85	0.94	0.79

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