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Detection of Dissolve transitions in High Quality Videos Using Histogram based Normalized Correlation Coefficients and Adaptive Threshold

[1]Kamal S. Chandwani, [2]Varsha Namdeo

[1]PhD Scholar, Sarvepalli Radhakrishnan University Bhopal, Madhya Pradesh, India
[2]Department of Computer Science & Engineering
Sarvepalli Radhakrishnan University Bhopal, Madhya Pradesh, India

[1]chandwani1@rediffmail.com, [2]varsha_namdeo@yahoo.com

Abstract – Rapid enhancements in Multimedia tools and features day per day have made entertainment amazing and the quality visual effects have attracted each and every individual to watch these days' videos. The fast-changing scenes, light effects and undistinguishable blending of diverse frames have created challenges to researchers in detecting gradual transitions. The state of art editing mechanism has made difficult to perceptually distinguish and application software's to highlight transitions between various scenes in videos due to marvellous mixing techniques available today. The proposed work is aimed to detect gradual transitions in videos using correlation coefficients obtained through color histograms and adaptive thresholding mechanism. Other gradual transitions including fade out, fade in, cuts are eliminated successfully and dissolves are found from the acquired video frames. The characteristics of normalized correlation coefficient are studied carefully and dissolve are extracted out in a simple manner with low computational and time complexity. The experimental results obtained over 14 videos with 25 dissolves proved remarkable in detecting 22 dissolve transitions successfully under lightning effects and object motions. The detection accuracy is affected when the start and end frame of the transition have deceptive similarity,similar of poor contrast background and large object motion over the original frame. The performance is measured in terms of precision, recall and F-measure.

Keywords – Multimedia tools, gradual transitions, correlation coefficients, color histograms, adaptive thresholding, fade out, fade in, cuts and dissolve.

1. Introduction

The challenges in video summarization and then retrieval had become the foremost need owing to rapid development in Multimedia technology. The development had introduced an extremely high quality techniques in video processing and certainly made difficult to extract meaningful segments from a video called shots. The greatest challenges introduced includes uneven illuminations, camera movements, object rotations, low contrast backgrounds, low frequency transitions etc. The most common approach used in video summarization involves pre- processing the video frames, extracting and selecting optimum features, finding correlation coefficients between successive or neighbouring frames, detecting transitions, identifying key frames, detecting and tracking objects, classification etc. Shots carry vital information regarding specific scenes and can be differentiated by detecting the abrupt transitions and the gradual transitions. Abrupt transitions are even perceptual and can be easily detected using simple algorithms when correlation between successive frames is evaluated. Gradual transitions are hard to isolate due to several effects introduced such as dissolves, fade in and out and wipes. Unlike abrupt transitions the correlation between successive frames in case of gradual transitions is very low that is the neighbouring frames shows high similarity. Detecting such gradual transitions, the transition effects have to be compensated and movements pertaining to objects and camera had to be cautiously handled. Various approaches as studied from the literature used key point detection in frames before finding the similarity between two successive frames. Patch matching with neighbouring patches is another sort of technique to perfectly locate the moving patch or region in the frames but requires high computational and time complexity.

Recently, researcher have focused their research on dissolve detection due to unacceptably high false hit rate. Most of them are based on histogram, pixel, edge etc. Histograms offer advantage since they are invariant to local motions or small global motions. (Lee et al., 2001) used threshold to determine transitions when it was applied to sum of absolute difference between two successive frames. The transition was declared when the sum was greater than the threshold. Similar approach was used by (Kilkukawa et. al. 1992, Nagasaka et al., 1992, Zhang et al., 1993). (Yoe and Liu, 1995) used adaptive threshold instead of fixed threshold based on sliding window. (Shahraray, B., 1995) proposed region based matching to determine the best match between two neighbouring frames. The frames were divided into 12 patches or regions to ensure extraction of motion vectors and weighted sum of sorted pixel difference was considered as the correlation between two frames. (Zhang et al., 1993) proposed a twin comparison method to compare two histograms based on histogram difference metric. (Boreczky and Rowe, 1996) used histogram with 64 bins and block based histograms in two stages. First stage global histograms were subtracted and their absolute value was compared with a threshold while in the subsequent stage the histogram difference metric was compared. The number of region differences exceeding the difference threshold when exceeded the count threshold, a transition was observed. (Yuan et al., 2007; Abdulhussain et al., 2018). Inter frame difference histogram based on poisson model to detect abrupt and gradual transitions was proposed by (Huo et al., 2016). (El Khattabi et al., 2017) introduced scale invariant feature transform to RGB color space while (Gargi et al., 2000) compared different Shot boundary detection schemes using color histograms as features. HSV histogram with level 5 difference was used to detect gradual transition in (Li et al., 2016). (Swanberg et al., 1993) used block based histogram over RGB color frames.

This paper is organized with the following headings: Related work covers state of art work contributed by different researchers: Methods and Materials deals with the proposed work and covers algorithm and complete description of the system: Results and Discussion includes experimental results obtained over different videos under test and performance parameters: and Conclusion focuses on the summary of the work, loopholes and future scope for the work.

2. Related Work

(Chakraborty D. et al., 2021) extracted frame features using principal component analysis to uplift prominent features and then subjected the features to distance calculating algorithm. The detection accuracy was then improved through reviewing false detection boundaries to convolutional neural network. (Jose J. et al., 2022) suggested to improve false detections of transitions and extract multiple invariant features such as scale invariant feature transform, color layout descriptor and edge change ratio. These features compensate the effect of variations in illumination, motion, scaling and rotation. The feature set was classified using SVM classifier to obtain F1-score of 97% over TRECVid 2007 dataset. (Suguna R. et al., 2022) segmented the frames into primary and candidate segments to analyse the transition behaviour in frames. Segmentation was obtained using color feature and local adaptive threshold of each part or segment. Speeded Up robust features extracted from boundary segments were utilized to fine-tune the transitions from the candidate segments over TRECVid 2001 dataset to achieve 90.8% F1-score in case of gradual transitions. (Wu et al., 2019) presented a two stage shot detection technique employing fusion of color histogram and deep features for distinguishing hard cuts and C3D based deep analysis to locate gradual cuts. Abrupt shots are used to partition the video into segments and 3D-convolutional neural network are used to classify the clips into specific gradual transitions. Merging techniques were used to know the positions of the gradual transitions.

(Wang et al., 2021) used three stage process to detect candidate boundaries, instant and gradual transitions through deep CNN. They improved the performance by filtering out many non- boundaries and introduced scheme to locate the start, mid and end point of the gradual transitions. (Bhaumik H. et al., 2017) introduced two phased approach to detect candidate dissolves and filter candidates based on threshold. The first stage involves identifying parabolic patterns in the mean fuzzy entropy of the frames and the second stage uses ensemble of four parameters for filtering, respectively. (H. M. Nandini et al., 2022) detected abrupt shots using Binarized edge information through linear binary pattern and estimating the Euclidean distance of the histogram features and then applying an adaptive threshold. For key frame extraction, a sobel operator was used to get the magnitude gradient of frames under a segmented shot and transformed into z-scores. The frame possessing the highest value corresponding to coefficient of variation was selected as the key frame for the shot.

Our Contribution

We propose a simple and efficient method to detect dissolves in high quality videos using correlation coefficient obtained from color histograms. The approach includes:

1. Finding normalized correlation coefficients between successive frames based on histograms obtained using color channels to locate abrupt and gradual cuts.

2. Isolating abrupt cuts, fade in and fade out and distinguishing dissolves based on the characteristics of normalized correlation coefficients with respect to an adaptive threshold.

3. Methods and Materials

The proposed work is concentrated in detecting dissolve transitions in videos based on calculating the consecutive frame differences and then thresholding the histogram obtained from the correlated values between such consecutive frames. Histogram for all three color components of two consecutive frames are considered for evaluating the correlated values by subtracting the histograms of individual color components, followed by taking the absolute values and finally finding the sum. The average value of all the three color component are then averaged, normalized using the maximum value and histogram corresponding to (N-1) correlated values is obtained. The maximum values in the (N-1) correlated values is found to for thresholding the (N-1) values. Finally the threshold correlated values are normalized again with respect to the maximum value. The flowchart of the proposed algorithm for detecting the dissolve transitions is shown in the figure 1 below.

The video under consideration is converted to frames and stored in a separate folder. We examined the dissolves in each video manually and noted the transition frames. Considering 'N' frames in a video, the correlated coefficients obtained will be (N-1) since the last frame have no frame to find the correlation after it. Histograms for each two consecutive frames are computed (viz. Red, Blue and the Green component) and difference of each of the component from the two frames is evaluated. The sum corresponding to the absolute values of the differences for two consecutive frames is then stored. The process is continued till frame (N- 1) is covered. We considered all the three values and the mean of those three values corresponding to three color components to represent the correlation between both the frames. The (N-1) array is normalized by dividing each of the value by the maximum value in the array.

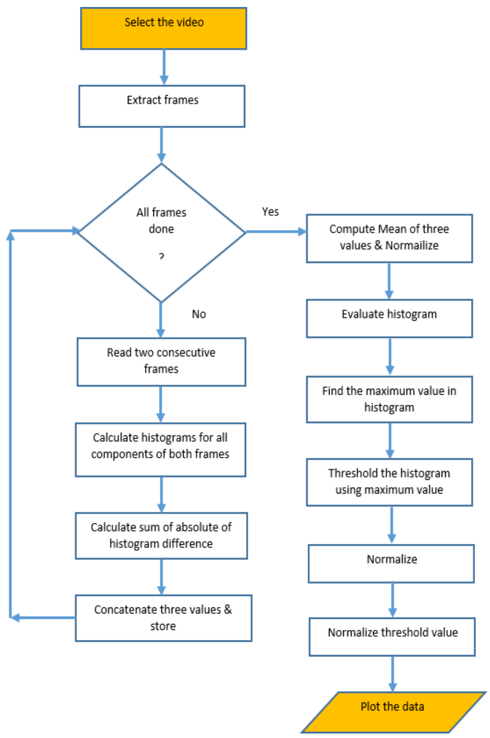

Figure 1 – Flowchart for the proposed algorithm to detect the Dissolve transitions

Considering the $frame_i$ to represent one of the two consecutive frames, the histogram h_c for any of the color component is given by expression (1), where H represent the histogram.

$h_{i\ c\ \epsilon\ (R,\ G,\ B)} = H\ (frame_i)\ \text{frame}_{\epsilon\ (R,\ G,\ B)}$ (1)

The correlation between two consecutive frames is thus obtained by the following expression (2),

$C_{x\ \epsilon\ (R,\ G,\ B)} = \text{sum}\ (\text{abs}\ (h_{ix} - h_{(i+1)\ x}))$ (2)

The correlated values are stored in an array D which can be represented by,

$D = \bigcup_{m=1}^{n=N-1}[C_R; C_B; C_G]$ (3)

The correlation coefficients are obtained by taking the average value of all three components and expressed using the following equation (4),

$M = \frac{1}{} \sum^{N-1} D$ (4)

R,G,B

The normalizing coefficient M_{max} is obtained by finding the maximum value in array M. Equation (5) finds the maximum value.

$M_{max} = \text{Max}\ (M)$ (5)

The correlation coefficients are normalized using the expression (6), $F = M/M_{max}$

(6)

Now we find the histogram of the normalized correlation coefficients using expression (7). $G = H\ (F)$ (7)

The adaptive threshold is then calculated using the maximum value in the histogram which is given by the following equation (8).

$T = \text{Max}\ (G)$ (8)

With this adaptive threshold T, the values in F are subjected to threshold using the expression (9).

$$S = \begin{cases} 1 & if\ F > T \\ 0 & Otherwise \end{cases} \quad (9)$$

The original values remaining after thresholding are obtained by multiplying the result obtained using equation (9) by F again, which can be represented by the equation (10).

$$S = S \times F \quad (10)$$

Finally the threshold T is made consistent with the values in S by dividing the threshold T with value 256.

$$T = T/256 \quad (11)$$

Histogram of normalized values is obtained further and the maximum value in the histogram is considered as a threshold. The threshold value is used to threshold the values of histogram and multiplied by values in histogram again. The threshold value is normalized by dividing it with value 256 to make it consistent with the histogram obtained in the previous stage. The following figure 2 depicts the plot for one of the video clip number 4 from Ashiqui song.

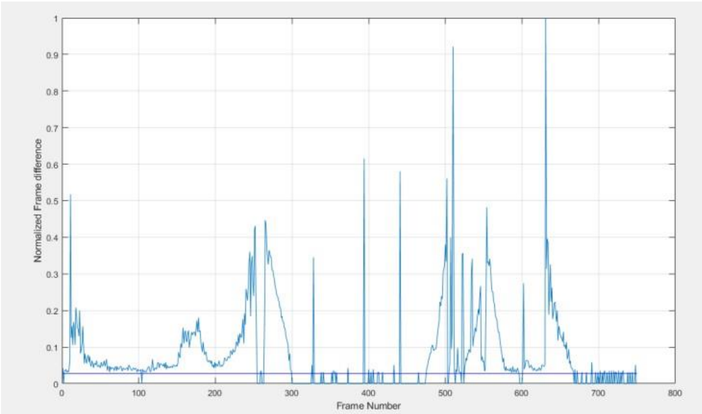

Figure 2 – Final plot obtained by our proposed algorithm on video clip 4 from film Ashiqui with horizontal base blue line as the Adaptive threshold

Dataset

We examined two video songs from Hindi movies 'Ashiqui' and 'Once Upon a time in Mumbai'. The videos were cut in smaller videos consisting of 500 to 800 frames. The reason behind is to reduce the computational and time complexity. The videos are so selected to test the effectiveness of our proposed algorithm since the songs are subjected to many object motions and varying illuminations are covers many dissolve, fade in, fade out and cuts transitions. We also separated video clips involving wipes but have not covered the detection of wipes in this work from other videos such as 'Star Wars 1', 'Star Wars 3', 'Bhootnath' and the 'Hidden Fortress'. Figure 3 shows a short dissolve transition from song Ashiqui. The number of frames are displayed as multiple of 5 but the actual number of frames containing dissolve are 13, which starts with 696th frame and end at 715th frame. All the videos have original frame rate of 25 frames per second.

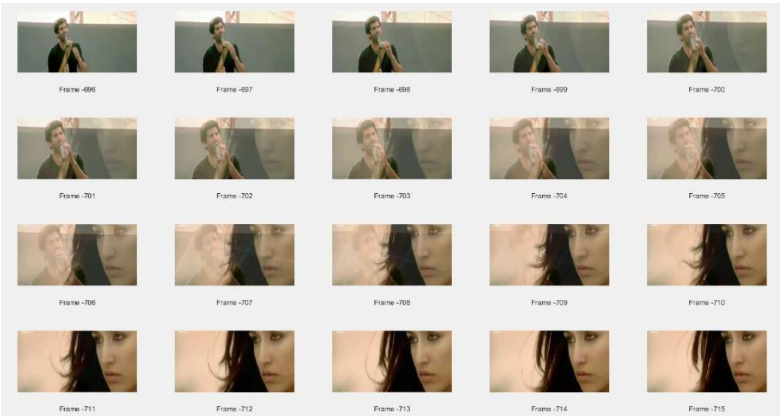

Figure 3 – A short dissolve (13 frames length) from HINDI movie 'ASHIQUI' from frames 696 to 715

The video clips used in this work and the manual results obtained for dissolve transitions are given in the Table I. For simplicity we have not mentioned other transitions as those are not part of this work such as fade in, fade outs and cuts. We have dealt with fade in and fade out in our earlier work (Chandwani K. et al., 2022). We achieved 100% accuracy in detecting fade in and fade out transitions.

Table I – Manually detected dissolve transitions in sample videos under consideration

Sr. No.	Film	Video	Frame Range for Dissolve Transitions
1	Ashiqui-2	Video Clip 1	655-690
2		Video Clip 2	110-130 380-400 431-450 561-585 630-650 700-721
3		Video Clip 3	30-80 100-135 413-440 696-711 728-750
4		Video Clip 4	None
5		Video Clip 5	None
6		Video Clip 6	None
7	Once Upon a time in Mumbai	Video Clip 11	None
8		Video Clip 12	99-120
9		Video Clip 13	140-175 197-235
10		Video Clip 14	None
11		Video Clip 15	25-55 64-100 105-140 204-235 244-280 290-325
12		Video Clip 16	81-110 135-120
13		Video Clip 17	None
14		Video Clip 18	1-20 618-645

4. Results and Discussion

Experimental evaluations carried on 14 videos containing rapid object motions and uneven illumination showed that our technique was able to detect the gradual transitions precisely. The nature of variation in normalized correlation coefficients using histogram technique as discussed earlier when dissolve is present is presented in figure 4. The correlation coefficients touches the adaptive threshold line during the start and end of the gradual transition and remains above the threshold during the dissolve transition. The same effect is observed in case of fade in and fade out transitions but there is an abrupt transition during the start and end frame. The effect of object motion and uneven illuminations are compensated using this technique. Slight spikes resulting from the object motion in dissolve transitions are unable to reach the threshold and thus identified as dissolves.

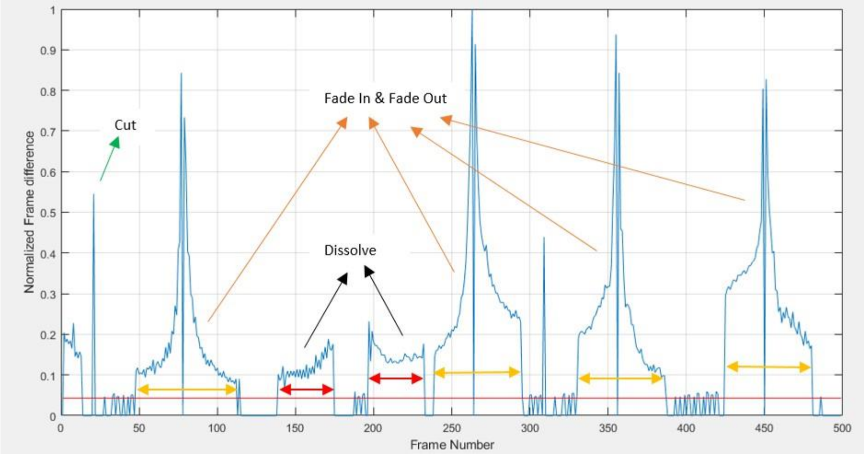

Figure 4 – Final plot obtained by our proposed algorithm on video clip 13 from film once upon a time in Mumbai with horizontal base blue line as the Adaptive threshold. The correlation coefficient characteristics for cut (green), dissolve (black) and fade in and fade out (orange).

As seen from figure 4, fade out followed by fade in as acquired by the correlated coefficients have different characteristics as compared to dissolve transitions. Dissolve transitions never touches the adaptive threshold line (Red) during the complete transition. Cuts are one frame spikes as indicated by the green arrow. The small spikes occurring between the start and end of any of the transitions are effects of object motion or due to difference of illuminations between successive frames. Following figures from 5 to 13 represents the nature of correlation coefficients plots obtained for other videos.

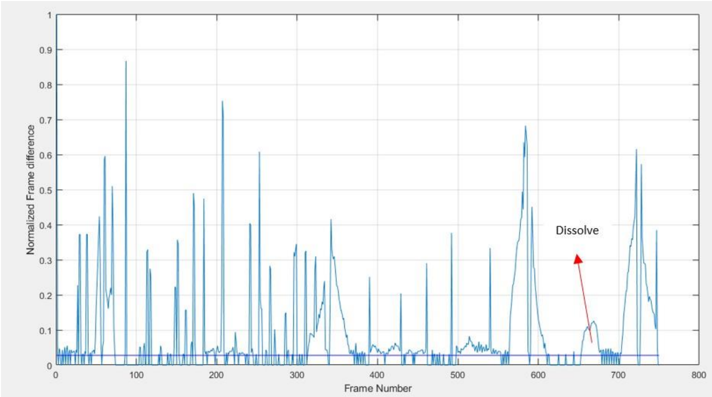

Figure 5 – Correlation Coefficients for Video 1 and the detected dissolve.

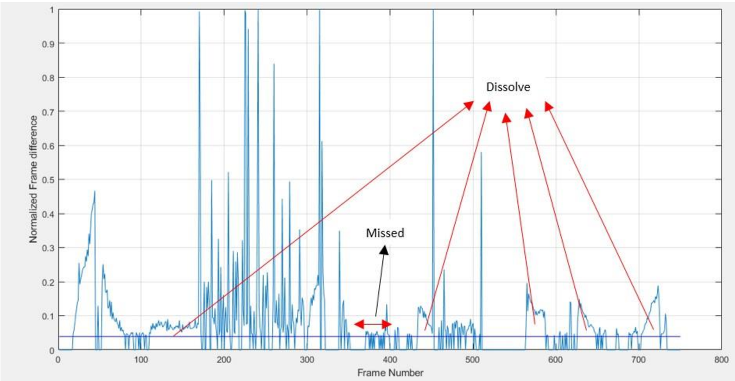

Figure 6 – Correlation Coefficients for Video 2 with Missed and detected dissolves.

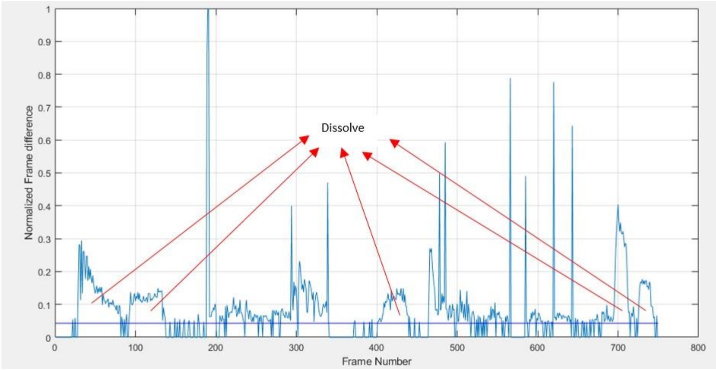

Figure 7 – Correlation Coefficients for Video 3 with detected dissolves.

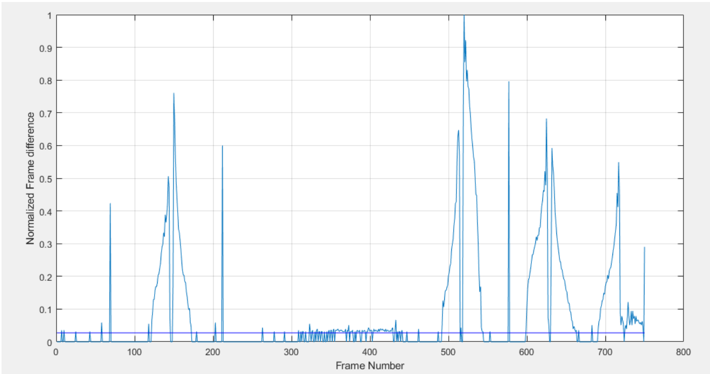

Figure 8 – Correlation Coefficients for Video 5 with no dissolve transitions.

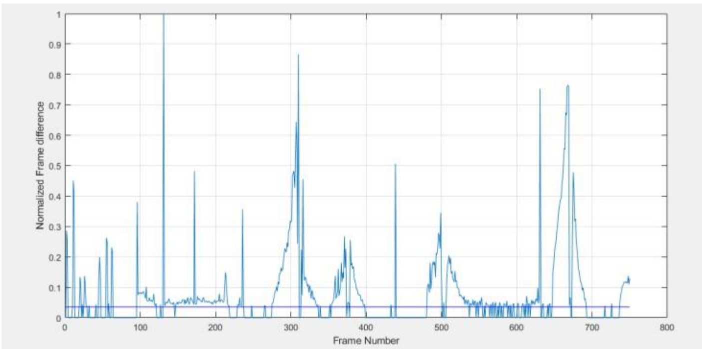

Figure 9 – Correlation Coefficients for Video 6 with no dissolve transitions.

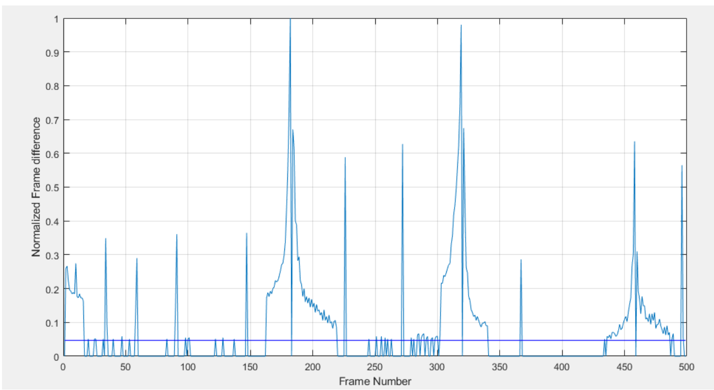

Figure 10 – Correlation Coefficients for Video 11 with no dissolve transitions.

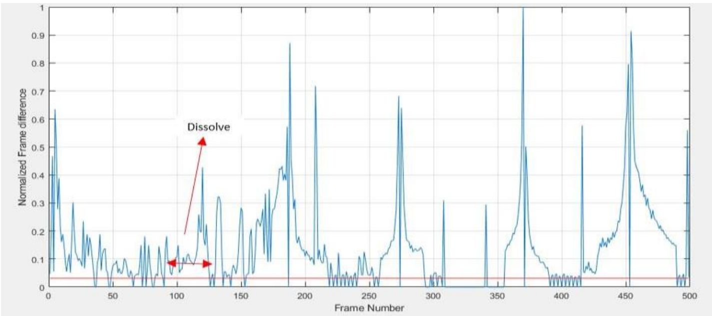

Figure 11 – Correlation Coefficients for Video 12 with no dissolve transitions.

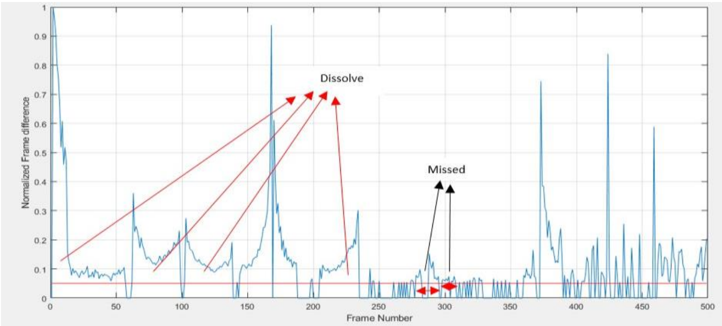

Figure 12 – Correlation Coefficients for Video 15 with Missed and detected dissolves.

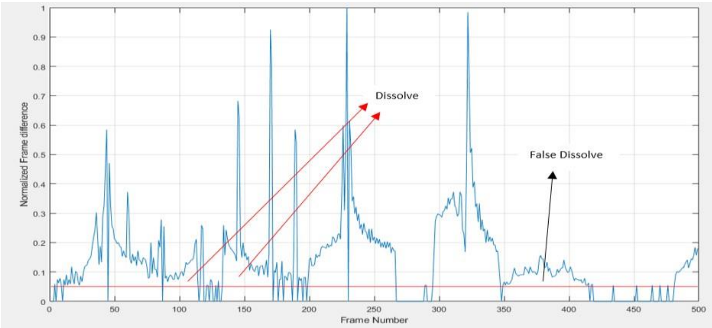

Figure 13 – Correlation Coefficients for Video 16 with False and True dissolves.

Video Clips 14 and 17 are not shown since they have no dissolve transitions and video clip 18 has two dissolve transitions but are accurately detected by our proposed system. Video clips 2 (Missed dissolve from frame 350 to 400) shows missed dissolved transitions due to reasons that there exists extreme illumination changes and camera motion. The undetected dissolves in video clip 15 (244-280 & 290-325) were due to densely populated objects and very slow transitions of similar types of frames at beginning and end of the transition. The similarity is due to the old frame being closely associated with the new frame as shown in the figure 14.

a. Start frame   b. Dissolve frame   c. Next frame

Figure 14 – Dissolve scene from video clip 15, where start frame and the new frame are closely associated with respect to illumination and background (dark)

The false dissolve in video clip 16 is due to motion of large object covering almost 80% of the significant frame. Advancement in multimedia technology no matter had improved the perceptual quality of videos and made the entertainment eye catching but at the same time increased the challenge in detecting transitions and almost impossible in some cases where the blending is done within few frames (less than 5-6 frames). Table II shows the results obtained using our technique.

Table II – Results obtained with our technique

Sr. No.	Film	Video Clip	Result with proposed Work	Discrepancies
1	Ashiqui	Video Clip 1	✓	
2		Video Clip 2	✓	Missed – (380-400)
3		Video Clip 3	✓	
4		Video Clip 4	✓	
5		Video Clip 5	✓	
6		Video Clip 6	✓	
7	Once upon a time in Mumbai	Video Clip 11	✓	
8		Video Clip 12	✓	
9		Video Clip 13	✓	
10		Video Clip 14	✓	
11		Video Clip 15	✓	Missed – (244-280, 290-325)
12		Video Clip 16	✓	False dissolve – (345-420)
13		Video Clip 17	✓	
14		Video Clip 18	✓	

Assuming TP for True positive samples, FP for false positive samples and FN for false negative samples.

Then, Precision P = $\frac{TP}{(TP+FP)}$ (12)

Recall R = $\frac{TP}{(TP+FN)}$ (13)

And, F-Measure F = $\frac{2*P*R}{(P+R)}$ (14)

Therefore, TP = 22, FP = 1, FN = 3 gives P = 22/24 = 0.9167, R = 22/(22+3) = 0.88 and F = (2x0.9167x0.88)/(0.9167 + 0.88) = 0.90.

5. Conclusions

Out of 14 video clips, with 25 dissolve transitions, the novel approach presented in this work was able to detect dissolve transitions in 11 videos having 22 dissolves with 100% accuracy. The video clips 4, 5, 6, 11, 14 and 17 were accurately determined by our technique which contained no such dissolve transitions. The reason for missed detection and false detection for videos 2, 15 and 16 had been quoted in the previous section. Thus our system for detecting gradual transitions in videos was successful in detecting 22 out of 25 transitions with an accuracy of approximately 92%. The precision, recall and F-measure are 0.9167, 0.88 and 0.90 respectively. The detection can be improved if the effect of illumination changes are compensated using any of the state of art contrast correction method and the effect of object motion is properly handled using robust correlation between neighbouring frames. We have not compared our results with any of the state of art techniques since our dataset is self- generated as to take into effect large illumination variations and object motions in video frames. We eliminated fade in and fade outs using our own technique presented in (Chandwani K. et al., 2022). The future work will be concentrated to improve the detection accuracy and eliminate false detection using extracting optimum features from the frames for finding correlations between neighbouring frames and deducing the feature vector for optimum detection.

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