Chapter 15
Modelling Fade Transition in a Video Using Texture Methods

Jharna Majumdar, N. R. Giridhar and M. Aniketh

1 Introduction

A video has a hierarchical structure, which when broken down to units have scenes, which is broken down to shots and shots are broken down to frames or images. A shot is an uninterrupted frame capture from a single video recorder. A video shot transition is a technique used to combine different shots in the film-making process to get a continuous flow in the video which is key to bring out certain emotions. These transitions may occur over a single frame or can occur over a number of frames. The transitions which occur over a single frame are called abrupt cut transition, whereas transitions which occur over a number of frames are called as gradual transitions. A gradual transition is of three types: fade, wipe and dissolve. A video shot transition detection also known as shot change detection is nothing but identifying changes in the scene content of a video sequence. The shot transition is the initial step for video segmentation, video summarization, video indexing and retrieval. Many techniques have been devised to detect an abrupt cut, but as the change of shot occurs over a sequence of frames in a soft transition, i.e. gradual transitions, detection of gradual transitions are not so easy and the algorithm becomes complex.Gajera and Mehta [1] in their paper have found gradual transition like Fade and Dissolve. The algorithm they have developed for Fade Transition calculated mean of DC image. Porter et al. [2] with the assistance of inter-frame coefficient and block-based movement estimation can locate the steady changes. This is done to track picture obstructs through the video sequence and to recognize changes caused by shot transitions. Truongt et al. [3] have presented enhanced algorithms for automatic fade and dissolve detection in video analysis. They have conceived new two-step

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calculations for fade and dissolve, and presented a technique for wiping out false positives from a rundown of distinguished applicant advances. Instead of selecting thresholds based on the traditional trial and error approach, robust adaptive thresholds are derived analytically from the mathematical models of transitions in Bansod et al. [4] have displayed a novel methodology for video shot detection, in light of the analysis of temporal slices which are extricated from the video by cutting through the sequence of video frames and gathering temporal signature.

Song et al. [5] with the help from Columbia's Consumer Video data set along with TRECVID 2014 Multimedia Event Detection data set have proposed an adaptive Support Vector Machine Model to extract the location of key segments from a video. Sun et al. [6] have presented a novel method for detecting cut transition and gradual transition. Their key idea employed is that a pixel in a frame usually has a pixel value close to it within its neighbourhood in the adjacent frame. It has a low computation complexity and it outperforms state-of-the-art methods. Fani et al. [7] have come up with an effective Shot Boundary Detection method for detecting both gradual and cut transitions. The candidate segment selection method is carried out by frame histogram and an adaptive threshold. This is done by the K-means classifier. To obtain discriminating feature vectors obtained from singular value decomposition along with some measures of differences are fed into a support vector machine. The gradient of a metric associated with each segment is evaluated to the boundary of the transition. Zhang et al. [8] have proposed an effective system for event recognition which is based on the semantic-visual knowledge base. From lexical database FrameNet and WordNet, event-centric concepts and the relationships between them are encoded. Later to learn the noise-resistant classifier a learning model is proposed. At last for the event representation, event-centric semantic concept is utilized. Zhu et al. [9] in their research work have given a unique tag to each shot, thus by solving video to shot tag problem. A Graph Sparse Group Lasso model is proposed to reconstruct visual features of test shots with that of training videos. From the learnt co-relations, a tagging rule is proposed. To build the model, constraints like temporal-spatial knowledge, intra-group sparsity and intergroup sparsity are considered. Duan et al. [10] in their proposed work have made an unsupervised approach for identification of video shots. Dictionary of features are extracted from small patches in a video called video words. Appropriate video words are selected for modelling by Information Projection. In the identification of the category of video shot by treating the problem as unsupervised graph partition task with each vertex of the graph representing a video shot. Stochastic Cluster Sampling technique is used for graph partition. Tippaya et al. [11] have proposed a multi-model visual feature-based shot boundary detection. It analyses the discontinuity signal to learn the behaviours of videos. It uses candidate segment selection to collect probable shots and the cumulative moving average of the discontinuity signal to identify shot boundaries. The proposed algorithm was tested on Sport and Documentary Video data set and was found to give high recall and precision values for cut transition detection and significant lower values for gradual transitions. Fu et al. [12] presents a novel—two-step—framework for shot transition detection. First Local Linear Embedding is used to extract manifold features. Addition of virtual frames is done to ensure embeddings that do not collapse to a single point. KNN classifier is used for the classification of transition. In this research paper, the authors have defined a new approach to detect Fade Transition following the principles of Machine Learning. It consists of two phases, the Learning Phase and Identification Phase. In the Learning Phase, each frame of the video sequence is transformed into a texture domain and the response of histogram properties [13] are analysed along with their gradient descent sign. Based on these observations, a rule is framed from which a polynomial is generated for all the input data set. In the Identification Phase, an unknown video sequence is fed as input to the system. The equation obtained in the polynomial equation is used here to identify if the video belongs to a transition or not. The remainder of this paper is structured as follows—Sect. 2 discusses Fade Transitions that can occur in a video. Section 3 deals with the methodology employed for this work, followed by experimentations and evaluations in Sect. 4 and Sect. 5, respectively.

2 Shot Transition

There are three types of gradual transitions: fade, dissolve and wipe. In this paper, we have focused our attention to Fade Transition. The methodology and the algorithm developed is given in the subsequent sections.

Fade Transition: A transition to and from a blank image is Fade. This is in contrast to a cut where there is no such transition. A gradual change between a scene and a steady picture (Fade-out) or between a consistent picture and a scene (Fade-in) (Fig. 1).

3 Methodology

3.1 Texture Methods

Image texture is characterized as a component of the spatial variation in pixel intensities (grey values). Image texture gives us data about the spatial arrangement of shading or greyscale distribution in an image or selected area of an image. In the current research work, we have made use of three texture methods namely Grey

Fig. 1 Fade transition

Level Co-occurrence Matrix (GLCM) [14], Statistical method [15] and Laws Texture method [16]. These methods are used to transform the video into different texture domains. Details of these methods are discussed in the appendix.

3.2 Extraction of Texture Features

3.2.1 Grey Level Co-occurrence Matrix (GLCM) [14]

It is a standout amongst the most known texture investigation techniques. Evaluations of picture properties are identified with second-order statistics. A Co-occurrence matrix is used to describe the patterns of neighbouring pixels in an image at a given distance, d. Every section (i, j) in GLCM relates to the number of occurrences of the pair of grey levels i and j which are at a separation d in the original picture. Co-occurrence matrix describes pixels that are

- adjacent to one another horizontally, $P^{0,}$
- vertical to one another horizontally, P^{90} and
- diagonal to one another horizontally, P^{45} and $P^{135.}$

Haralick has proposed 14 features out of which we make use six features, i.e. energy, entropy, contrast, maximum probability, variance and homogeneity (Appendix 1). Figure 2 shows the six features.

3.2.2 Statistical Method [15]

The factual strategy estimates the coarseness and directionality of texture. In any case, the statistical technique portrays the shape and distribution of the entities. Its produces geometrical properties of connected regions in a sequence of binary images. NOC_0 (mean), NOC_0 (variance), NOC_1 (mean) and NOC_1 (variance) are the four different properties (Appendix 2). Figure 3 shows the Statistical Texture method features.

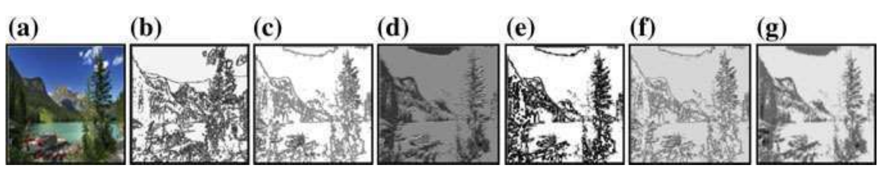


Fig. 2 GLCM texture features, **a** input image, **b** energy, **c** entropy, **d** contrast, **e** max probability, **f** homogeneity, **g** variance

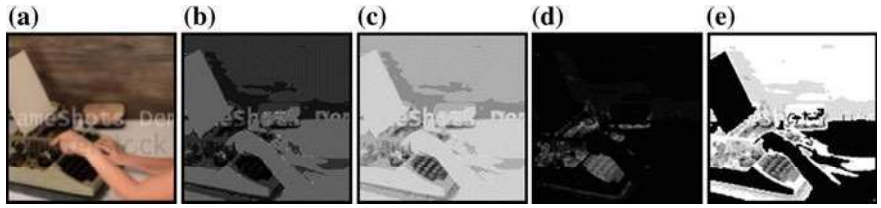


Fig. 3 Statistical texture method features. **a** Input image, **b** NOC_1 variance, **c** NOC_1 mean, **d** NOC_0 variance, **e** NOC_0 mean

3.2.3 Laws Energy Texture [16]

Laws portrayed a novel Texture energy approach to deal with texture analysis.

Laws Texture Energy feature purposes of high 'Texture energy' in an image. The two-dimensional convolution kernels regularly utilized for texture discrimination are created from the accompanying arrangement of one-dimensional convolution kernels of length 5:

- `L5 = [1 4 6 4 1]`
- `E5 = [-1 -2 0 2 1]`
- `S5 = [-1 0 2 0 -1]`
- `W5 = [-1 2 0 -2 1]`
- `R5 = [1 -4 6 -4 1]`

These mnemonics stand for Level, Edge, Spot, Wave and Ripple. From these one-dimensional convolution kernels, we can produce 25 diverse two-dimensional kernels. These are rotationally variant, so some of these kernels are combined to form convolution kernels which are invariant to rotation. The ten kernels obtained after combining, are rotationally invariant (Appendix 3). Figure 4 shows the Laws Texture features.

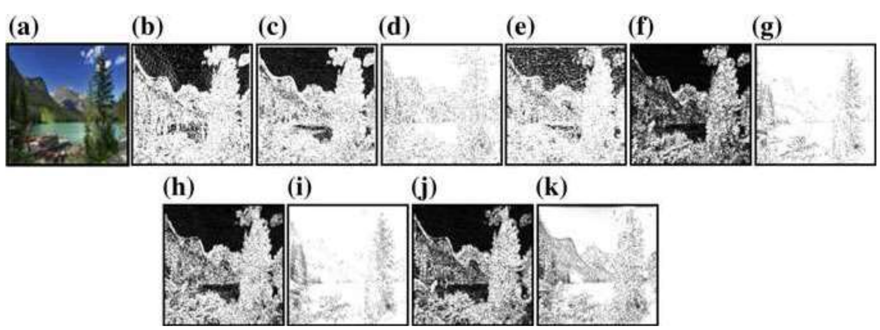


Fig. 4 Laws texture features. **a** Original image, **b** F1, **c** F2, **d** F3, **e** F4, **f** F5, **g** F6, **h** F7, **i** F8, **j** F9, **k** F10

3.3 Machine Learning for Video Transition

The objective of this work is to model Fade Transition in a video using video transformed in texture domain. The modelling is carried out in two phases: Learning Phase and Identification Phase. In order to propose the idea behind this research, we have considered Energy feature from the GLCM Texture method. For each frame of input video containing Fade Transition, we extract Texture Feature Energy to generate new video which corresponds to Energy feature from GLCM Texture. To analyse the response of new video during the transition and to formulate the rules, for each frame of transformed video we calculate characteristic properties of histogram such as Entropy, Skewness, Kurtosis and Spatial Frequency [13]. During the transition, we study the response of each frame of transformed video by observing the change of the value of characteristic properties of the histogram. We use gradient descent to study the nature of change.

3.4 Learning Phase

The entire process of detecting transition follows the principle of Machine Learning. A large number of videos from different categories containing Fade Transition is used as the input for the learning phase. Using the texture methods described in Sect. 3.2, such as Grey Level Co-occurrence Matrix (GLCM), Statistical Texture and Laws Texture Energy, the response of the gradient descent of histogram features is studied to form the rules. To start with, input video containing 'Fade Transition' is converted to texture domain and histogram properties [13] are calculated for each transformed frame. Property values are normalized within the range 0–1 for the ease of comparison. A graphical representation is done to observe the response of the histogram properties during the transition [13]. Based on the response of these properties, rules are formulated using gradient descent which is found to be consistent for any categories of video. The consistent response here refers to those rules which are unique for each transition and whose response is the same for different categories of the video. The same is shown in Fig. 5a.

In GLCM Texture, Energy, Homogeneity and Maximum Probability features gave consistent response for Fade Transition. In Laws Texture Energy, texture features F5 showed a consistent response to Fade Transition. Statistical Texture failed to produce any output and the same will be shown in the result section. These selected texture features are used in the Learning Phase to study the response of Fade Transition for any unknown video.

As an example, GLCM Texture's Energy feature is applied to the input frame sequence as shown in Fig. 6. The input video now corresponds to Texture Feature Energy of GLCM Texture method. For these frames, normalized values of histogram properties are plotted. The graph of the individual property will vary, but their behaviour will remain the same. Figure 7 shows the response of Skewness and

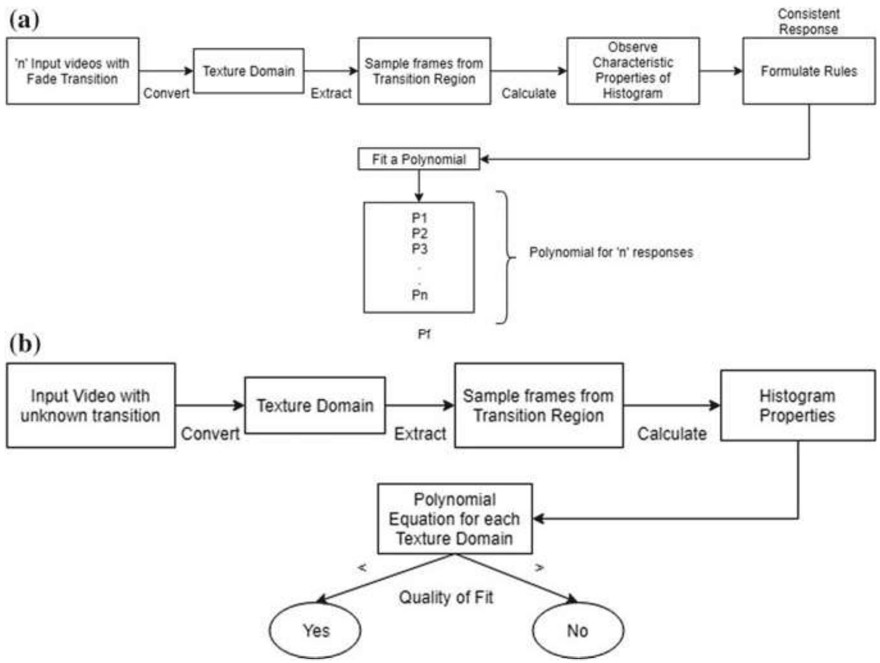
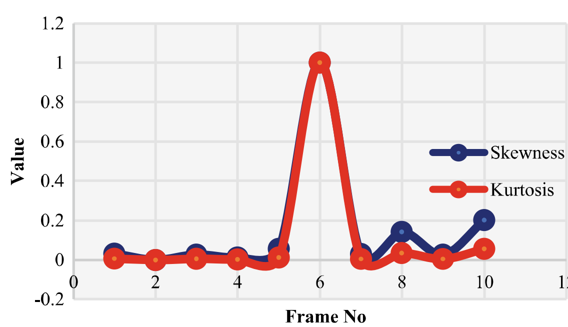


Fig. 5 **a** Pictorial Representation of learning phase, **b** pictorial representation of identification phase

Fig. 6 Input frame sequence for FADE transition

Fig. 7 The response of skewness and Kurtosis for GLCM texture's energy feature for video sequence shown in Fig. 6



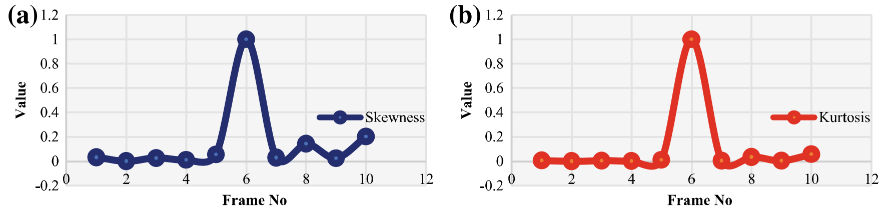


Fig. 8 **a** Response of skewness, **b** response of Kurtosis for GLCM texture's energy feature

Kurtosis. Figure 8a, b shows the response of Skewness and Kurtosis, respectively. Now the gradient descent (next frame—present frame) of two successive frames of an individual property is considered, i.e. the difference between the frames. If the difference is greater than or equal to 0, the gradient descent sign is set to +1. If the difference is less than 0, the gradient descent is set to –1. The normalized values of Skewness and Kurtosis are shown in Fig. 9a and c, respectively. Similarly, the gradient descent sign of Skewness and Kurtosis are shown in Fig. 9b and d, respectively.

The gradient descent values of the histogram properties are considered to formulate the rules. From Fig. 9b and d, we can observe the gradient descent sign values of Skewness and Kurtosis. It is seen that they are almost the same.

From this observation we can conclude that the responses of Skewness and Kurtosis have a linear relationship, i.e. they follow each other. The relationship is found out for four other input data containing Fade Transition. So, a plot of Skewness versus Kurtosis is obtained.

The above graphs show the plot of five input Fade Transition videos. Figure 10a shows the data obtained from the input videos, (b) corresponds to the polynomial obtained for the data obtained. The

Fig. 9 **a** Value of skewness for each frame, **b** gradient descent of skewness, **c** value of Kurtosis for each frame, **d** gradient descent of Kurtosis

(a)

0.032
0
0.026
0.011
0.05
1
0.02
0.14
0.03
0.20

(b)

+1
-1
+1
-1
-1
+1
-1
+1
-1

(c)

0.001
0
0.005
0.022
0.01
1
0.005
0.034
0.004
0.06

(d)

+1
-1
+1
-1
-1
+1
-1
+1
-1

Table 1 Polynomial coefficients for equation 1

a_0	−0.005
a_1	−0.4276
a_2	31.842
a_3	−350.81
a_4	1758.81
a_5	−4709.1
a_6	7270.58
a_7	−6531.5
a_8	3187.19
a_9	−655.57

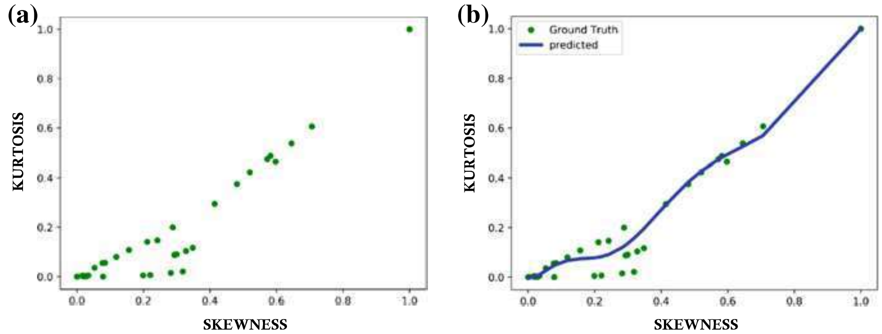


Fig. 10 **a** Experimental data, **b** experimental data with polynomial fit

respective polynomial equation for curve shown in Fig. 10b is $k = a_0 + a_1 s + a_2 s^2 + a_3 s^3 + a_4 s^4 + a_5 s^5 + a_6 s^6 + a_7 s^7 + a_8 s^8 + a_9 s^9$; equation 1; k: kurtosis, s: skewness.
The respective polynomial coefficients are shown in Table 1.

Hence is the rule that is formulated

(1) Skewness and Kurtosis have a linear relationship, i.e. they follow each other.

3.5 *Verification Phase*

With the help of polynomial obtained in the Learning Phase, it is verified if the output obtained for Kurtosis matches with that of experimental Kurtosis data (Figs. 11, 12 and 13).

(a)	(b)	(c)
0.032	0.001	0.001
0	0	0
0.026	0.005	0.005
0.011	0.022	0
0.05	0.01	0.021
1	1	0.99
0.02	0.005	0.001
0.14	0.034	0.072
0.03	0.004	0.007
0.20	0.06	0.078

Fig. 11 **a** Experimental data of skewness, **b** experimental data of Kurtosis, **c** data of Kurtosis obtained from the Polynomial equation 1

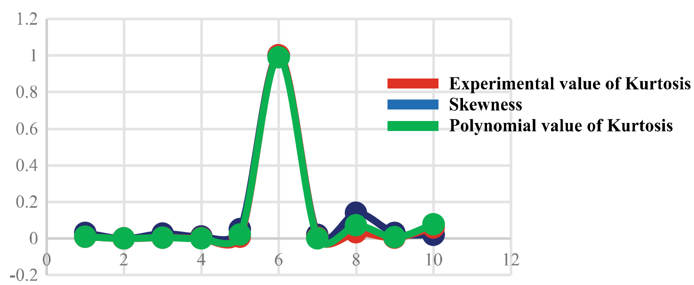


Fig. 12 Representation of all the three data shown in Fig. 11

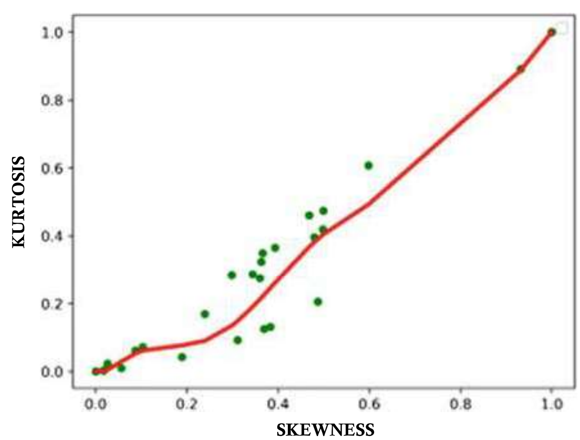


Fig. 13 The plot of skewness versus Kurtosis for four input data sets

Table 2 Quality of Fit values for five data sets in Learning Phase and four data sets in Identification phase

Quality of fit	Learning phase	Identification phase
SSE	0.07297	0.07369
MSE	0.001459	0.00184
RMSE	0.03819	0.04289

3.6 Identification Phase

In this phase, the polynomial equation along with the rules from Learning Phase is used to detect the kind of transition the video belongs to. Feature corresponding to texture method which gives a consistent response from a video of different categories is selected as the rules during Learning Phase. These rules are verified with known data in Learning Phase. Given a raw input video, using the rules obtained in the Learning Phase, we can identify the type of video the transition belongs to. For GLCM, Energy Texture feature, the corresponding polynomial equation is represented in equation 1 and coefficients are shown in Table 1. The rule obtained is

(1) Skewness and Kurtosis have a linear relationship, i.e. they follow each other.

In this phase, a total of four fade data sets are used as input. To measure the quality of polynomial fit, Sum of Squared due to Errors (SSE), Mean Square Error (MSE) and Root Mean Squared Error (RMSE) are used.

Green dots represent the actual value of Kurtosis with Skewness obtained. The red line is the curve that is generated using the values of Skewness to the polynomial obtained in the Learning Phase. From each video sequence, 10 frames are used. So a total of 40 frames are used (Table 2).

4 Experimental Study and Results

A total of 30 videos from various categories are trained. A total number of videos from Fade, Dissolve and Wipe are 10 each. The number of inputs to the Learning Phase is 5 and to that of Identification Phase is 4. To obtain texture features which are consistent to Fade Transition, a total of 1500+ graphs were analysed. In this section, we have presented the results in three parts.

Part I: Modelling Fade Transition using Grey Level Co-occurrence Matrix (GLCM) Texture

Feature: Homogeneity

Learning Phase
The algorithm discussed in Section II—D is implemented for 5 input data sets containing Fade Transition. The input video is converted to GLCM's Homogeneity Feature.

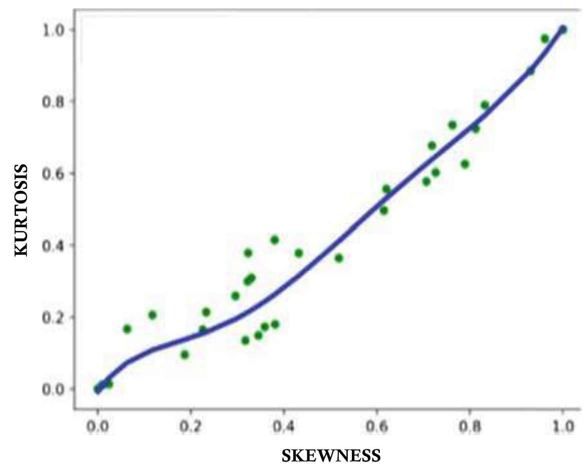


Fig. 14 The plot of skewness versus Kurtosis

Figure 14 represents the plot of Skewness versus Kurtosis. Green dots represent the experimental data and the blue curve represents the polynomial obtained for the experimental data. Rule obtained is

(1) Skewness and Kurtosis have a linear relationship, i.e. they follow

The respective polynomial equation for the curve shown in Fig. 14 is $k = a_0 + a_1 s + a_2 s^2 + a_3 s^3 + a_4 s^4 + a_5 s^5 + a_6 s^6$; equation 2; k: kurtosis, s: skewness. The respective polynomial coefficients are

Identification Phase

The polynomial equation 2 obtained in the Learning Phase is used here. Green dots represent the actual value of Kurtosis with Skewness obtained. The red line is the curve that is generated using the values of Skewness to the polynomial obtained in the Learning Phase (Fig. 15).

Feature: Maximum Probability

Learning Phase

The algorithm discussed in Section 3 is implemented for five input data sets containing Fade Transition. The input video is converted to GLCM's Maximum Probability.

Figure 16a represents the plot of Skewness versus Kurtosis, (b) represents the plot of Entropy versus Spatial Frequency. Green dots represent the experimental data and the blue curve represents the polynomial obtained for the experimental data. Rule obtained is

1. Skewness and Kurtosis have a linear relationship, i.e. they follow each other.
2. Entropy and Spatial Frequency have a linear relationship, i.e. they follow each other.

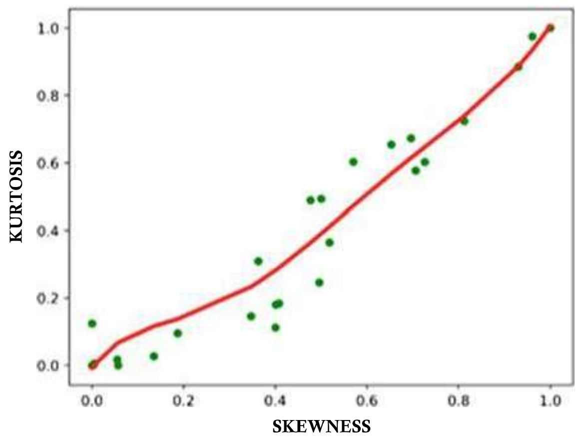


Fig. 15 The plot of skewness versus Kurtosis

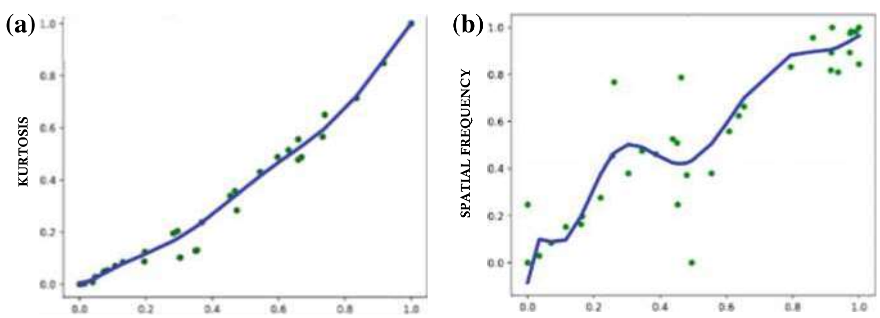


Fig. 16 **a** The plot of skewness versus Kurtosis, **b** plot of entropy versus spatial frequency

The respective polynomial equation for curve shown in Fig. 16a is $k = a_0 + a_1 s + a_2 s^2 + a_3 s^3 + a_4 s^4 + a_5 s^5 + a_6 s^6 + a_7 s^7 + a_8 s^8$; equation 3; k: kurtosis, s: skewness. The respective polynomial coefficients are

The respective polynomial equation for curve shown in Fig. 16b is $sf = a_0 + a_1 e + a_2 e^2 + a_3 e^3 + a_4 e^4 + a_5 e^5 + a_6 e^6 + a_7 e^7 + a_8 e^8 + a_9 e^9 + a_{10} e^{10}$; equation 4; sf: spatial frequency, e: Entropy. The respective polynomial coefficients are

Identification Phase

The polynomial equations 3 and 4 obtained in the Learning Phase is used here. In Fig. 17a, green dots represent the actual value of Kurtosis with Skewness obtained. The red line is the curve that is generated using the values of Skewness to the polynomial obtained in the Learning Phase. Similarly, in Fig. 17b green dots represent the actual value of Spatial Frequency with Entropy obtained.

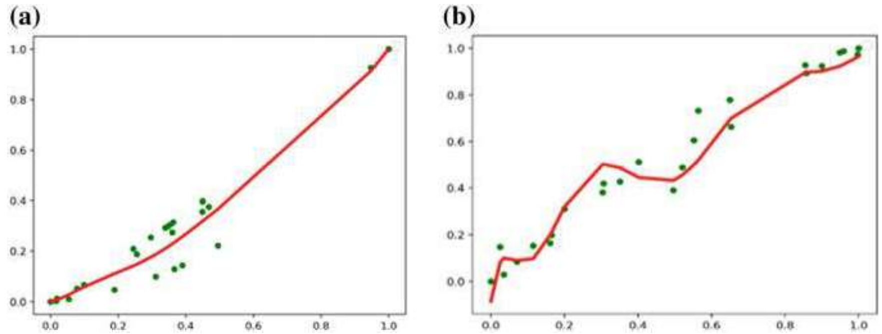


Fig. 17 **a** Plot of skewness versus Kurtosis, **b** plot of entropy versus spatial frequency

The red line is the curve that is generated using the values of Entropy to the polynomial obtained in the Learning Phase.

Part II: Modelling Fade Transition using Laws Texture method

Feature: F5
Learning Phase
The algorithm discussed in Section 3 is implemented for five input data sets containing Fade Transition. The input video is converted to Laws F5 feature.

Figure 18 represents the plot of Skewness versus Frequency. Green dots represent the experimental data and the blue curve represents the polynomial obtained for the experimental data. Rule obtained is

(1) Skewness and Spatial Frequency invert each other.

Fig. 18 The plot of skewness versus spatial frequency

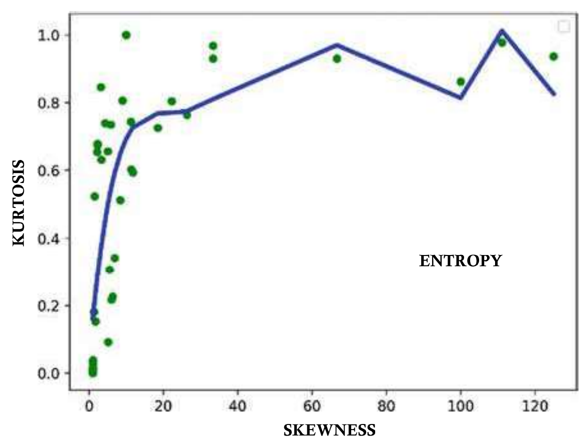
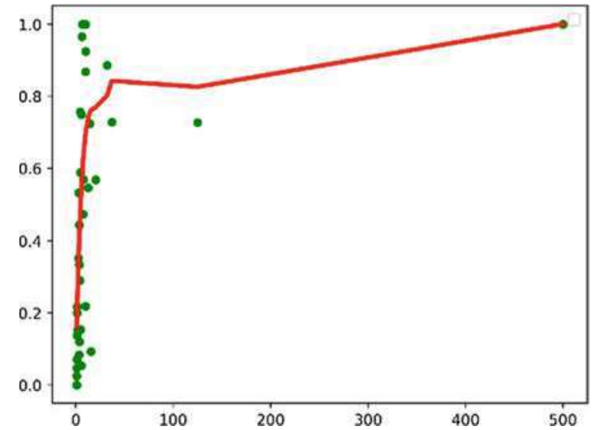


Fig. 19 The plot of skewness versus spatial frequency



The respective polynomial equation for the curve shown in Fig. 18 is $p = a_0 + a_1 s_i + a_2 s_i^2 + a_3 s_i^3 + a_4 s_i^4 + a_5 s_i^5 + a_6 s_i^6 + a_7 s_i^7$; equation 5; p: spatial frequency, $s_i : \frac{1}{skewness}$; The respective polynomial coefficients are

Identification Phase
The polynomial equation 5 obtained in the Learning Phase is used here. Green dots represent the actual value of Spatial Frequency with Skewness obtained. The red line is the curve that is generated using the values of Skewness to the polynomial obtained in the Learning Phase (Fig. 19).
The algorithm discussed in Section 3 is implemented for five input data sets containing Fade Transition. The input video is converted to Laws' F5 feature.

Feature: F3
Learning Phase
The algorithm discussed in Section 3 is implemented for five input data sets containing Fade Transition. The input video is converted to Laws' F3 Feature. Figure 20 represents a plot between Contrast and Entropy for Laws' F3 Feature. The experimental data are spread all over the graph. So, it is not possible to fit a polynomial to obtain a relationship between Contrast and Entropy.

Part III: Modelling Fade Transition using Statistical Texture Method

Feature: Variance NOC1
Learning Phase
The algorithm discussed in Section II—D is implemented for five input data sets containing Fade Transition. The input video is converted to Statistical's Variance N0C1 feature.

Figure 21 represents a plot between Contrast and Entropy for Statistical's Variance N0C1 feature. The experimental data are spread all over the graph. So, it is not possible to fit a polynomial to obtain a relationship between Mean and Kurtosis (Tables 3, 4, 5 and 6).

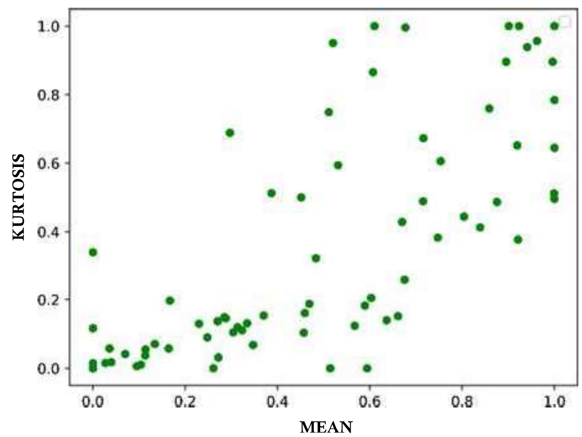


Fig. 20 The plot between contrast and entropy

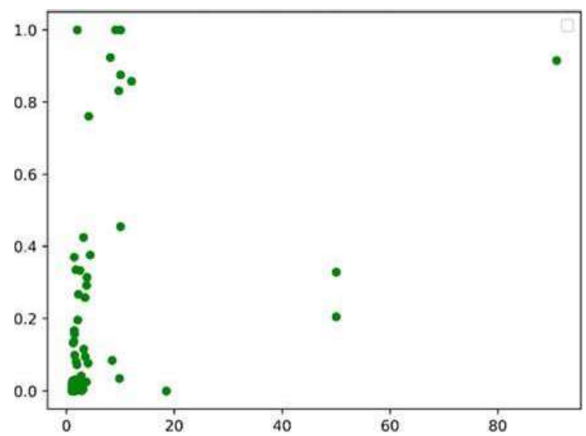


Fig. 21 The plot between mean and Kurtosis

Table 3 Polynomial coefficients for equation 2

a_0	−0.0076
a_1	1.7989
a_2	−10.251
a_3	33.318
a_4	−46.899
a_5	29.9741
a_6	−6.9272

Table 4 Quality of fit values for five data sets in learning phase and four data sets in identification phase

Quality of fit	Learning phase	Identification phase
SSE	0.14671	0.18858
MSE	0.00293	0.00471
RMSE	0.05413	0.006863

Table 5 Polynomial coefficients for equation 3

a_0	0.0005
a_1	0.20599
a_2	8.77101
a_3	−73.192
a_4	286.698
a_5	−577.19
a_6	620.688
a_7	−338.16
a_8	73.189

Table 6 Polynomial coefficients for equation 4

a_0	−0.085
a_1	11.686
a_2	−258.06
a_3	2539.58
a_4	−12630
a_5	36146.7
a_6	−63669
a_7	70633.4
a_8	−48384
a_9	18788.8
a_{10}	−3176.7

On comparing the quality of polynomial fit from Tables 2, 4, 7 and 8, Feature Maximum Probability of GLCM Texture gives the best result. The respective rule is

(1) Skewness and Kurtosis have a linear relationship, i.e. they follow each other.

Table 7 Quality of Fit values for five data sets in learning phase and four data sets in identification phase for skewness and Kurtosis

Quality of fit	Learning phase	Identification phase
SSE	0.0462	0.11279
MSE	0.000924	0.002819
RMSE	0.0304	0.05309

Table 8 Quality of fit values for five data sets in learning phase and four data sets in Identification phase for entropy and spatial frequency

Quality of fit	Learning phase	Identification phase
SSE	0.78801	0.15179
MSE	0.01576	0.00379
RMSE	0.12554	0.006156

5 Evaluation

The previous section concluded that polynomial 4, i.e. Feature Maximum Probability of GLCM Texture gives the best result. In this section, we feed in three Fade videos in order to evaluate the result obtained.

Fade video 1

Fade video 2

Fade video 3

The algorithm discussed in Section II—D is implemented for Frame Sequence shown in Figs. 22, 23 and 24. Each input video is converted to GLCM's Maximum Probability feature. Polynomial 4 obtained in Sect. 4 is evaluated (Tables 9, 10, 11, 12, 13, 14, 15 and 16).

Fig. 22 Fame sequence of fade transition

Fig. 23 Fame sequence of fade transition

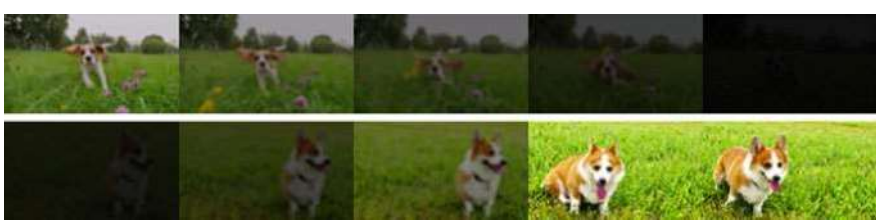


Fig. 24 Fame sequence of fade transition

Table 9 Polynomial coefficients for equation 5

a_0	0.0443
a_1	0.1259
a_2	−0.0084
a_3	0.00027
a_4	−4.38e−06
a_5	3.54e−08
a_6	−1.30e−10
a_7	1.49e−13

Table 10 Quality of fit values for five data sets in learning phase and four data sets in identification phase

Quality of fit	Learning phase	Identification phase
SSE	0.14671	0.18858
MSE	0.00293	0.00471
RMSE	0.05413	0.006863

Table 11 Experimental data of skewness and Kurtosis along with the value of Kurtosis obtained from polynomial 4 for fade video 1

Skewness	Kurtosis (Experimental)	Kurtosis (Polynomial)
0	0	0.0005
0.10031	0.0455515	0.0593063
0.471687	0.303246	0.341571
0.505725	0.334882	0.376819
0.461615	0.293567	0.331025
1	1	1.01048
0.851823	0.756121	0.751584
0.738473	0.595775	0.598527
0.511025	0.340736	0.382219
0.410735	0.249803	0.278134

Table 12 Quality of Fit for Table 11

SSE	0.0074816
MSE	0.00074816
RMSE	0.0273525

6 Conclusion

Texture methods can individuate Fade Transition from the rest. Grey Level Co-occurrence Matrix (GLCM) and Laws Texture Energy gave a consistent response to differentiate Fade Transition from the rest when compared to our previous work [13] which made use of histogram properties. The methodology discussed in this work

Table 13 Experimental data of Skewness and Kurtosis along with the value of Kurtosis obtained from Polynomial 4 for Fade video 2

Skewness	Kurtosis (Experimental)	Kurtosis (Polynomial)
0.614324	0.330269	0.480712
0.970193	0.928107	0.961538
1	1	1.01048
0.997019	0.994909	1.00587
0.42334	0.161315	0.291072
0.391485	0.140276	0.258789
0.364271	0.123274	0.232619
0.312565	0.0957368	0.188129
0.112854	0.0223466	0.0673987
0	0	0.0005

Table 14 Quality of Fit for Table 13

SSE	0.0773857
MSE	0.00773857
RMSE	0.0879691

Table 15 Experimental data of skewness and Kurtosis along with the value of Kurtosis obtained from polynomial 4 for fade video 3

Skewness	Kurtosis (Experimental)	Kurtosis (Polynomial)
0.730343	0.574893	0.589797
0.612519	0.433578	0.479086
1	1	1.01048
0.865577	0.768754	0.774424
0.559894	0.377597	0.430417
0.637257	0.458815	0.501282
0.988982	0.987114	0.993093
0.923623	0.870971	0.877688
0	0	0.0005
0.0210997	0.0107535	0.0081181

Table 16 Quality of fit for Table 15

SSE	0.00711661
MSE	0.000711661
RMSE	0.026677

is to be applied to Dissolve and Wipe Transition to see their behaviour. In this paper we have explored only texture domain; other domains like Wavelet should also be explored.

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Appendix 1

Grey level Co-occurrence matrix (GLCM) Haralick has proposed 14 features out of which we use six features which are as follows:

(1) *Energy*: Angular Second Moment is also known as Uniformity or Energy. It is the sum of squares of entries in the GLCM. $Energy = \sum_{i,j=0}^{N-1} P_{i,j}^2$

(2) *Entropy*: Entropy shows the amount of information of the image that is needed for the image compression. $Entropy = \sum_{i,j=0}^{N-1} P_{i,j}\left(-ln P_{i,j}\right)$

(3) *Contrast*: Contrast is defined as the difference between the highest and the smallest values other adjacent set of pixels considered. $Contrast = \sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2$

(4) *Maximum Probability*: This simple statistic records in the centre pixel of the window, the largest P_{ij} value found within the window. $MP = Max\left(P_{i,j}\right)$

(5) *Homogeneity*: Homogeneity weighs values by the *inverse* of the Contrast weight, with weights decreasing exponentially away from the diagonal. $Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}$

6) *Variance*: Variance is a measure of the dispersion of the values around the mean. It is similar to entropy. $Variance, \sigma_j^2 = P_{i,j}(j - \mu_j)^2 \quad \mu_j = \sum_{i,j}^{N-1} j(P_{i,j})$

Appendix 2

Statistical Texture method

The two geometrical attributes NOC_1 (α) and NOC_0 (α) are characterized using the following formulas:

1. Sample mean $\frac{1}{\sum_{\alpha=1}^{n_l-1} g(\alpha)} \sum_{\alpha=1}^{n_l-1} \alpha \cdot g(\alpha)$
2. Sample variance $\frac{1}{\sum_{\alpha=1}^{n_l-1} g(\alpha)} \sum_{\alpha=1}^{n_l-1} (\alpha - sample\_mean)^2 . g(\alpha)$

Appendix 3

Laws features

The 25 kernels are rotationally variant so some of these kernels are combined to form convolution kernels which are invariant to rotation. The invariance of rotation has a major impact on pattern recognition, pattern classification, etc.

So we will denote these new features with an appended 'R' for 'rotational invariance'.

E5L5TR = E5L5T + L5E5T (F1)
S5L5TR = S5L5T + L5S5T (F2)
W5L5TR = W5L5T + L5W5T (F3)
R5L5TR = R5L5T + L5R5T (F4)
S5E5TR = S5E5T + E5S5T (F5)
W5E5TR = W5E5T + E5W5T (F6)
R5E5TR = R5E5T + E5R5T (F7)
W5S5TR = W5S5T + S5W5T (F8)
R5S5TR = R5S5T + S5R5T (F9)
R5W5TR = R5W5T + W5R5T (F10)

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