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# A Comprehensive Survey on Detection of Video Transitions

Ayushi P. Yeram[1,*], Shrikant P. Chavate[2]

**_Abstract_**

*Video shot boundary detection (SBD) is a fundamental task in the field of video processing and analysis. It plays a critical role in various video applications such as content-based video retrieval, video indexing, editing, summarization, and browsing. Identifying shot boundaries helps segment a continuous video stream into distinct shots, each representing a meaningful visual unit. This segmentation is essential for organizing and interpreting video data efficiently. This study provides an in-depth review of the techniques and methodologies applied in shot boundary detection, with particular attention to the detection of gradual transitions such as wipes and dissolves. These types of transitions are often more challenging to detect compared to abrupt cuts due to their subtle and progressive nature. The study examines various preprocessing methods, feature extraction techniques, and similarity measurement approaches used to accurately detect these gradual transitions. Furthermore, the study analyzes and compares the performance of different SBD methods based on standard evaluation metrics such as precision, recall, and F1-score. A comparative review of several benchmark datasets is also presented to highlight the effectiveness of each method. This comprehensive analysis aims to guide researchers and developers in choosing the most appropriate techniques for specific video analysis applications.*

**Keywords:** Walsh-Hadamard transform, speeded-up-robust feature, dynamic mode decomposition, convolutional neural network, Squared Tchebichef-Krawtchouk polynomial, Kirsh directional derivative, singular value decomposition, sparse coding

## INTRODUCTION

Every video stream is made up of several shots, each of which is a series of frames captured by a single camera. Changing from one camera to another is necessary to move from one shot to the next. Scene change or shot boundary detection is the term used to describe the identification of these transitions. It is the initial stage of any system that analyzes video streams. Multimedia gadgets, advanced communication technology and inexpensive storage devices are reasons behind the recent surge in the quantity of videos accessible online. These videos are merely text annotated and stored in databases. The way videos are stored in databases makes content based video browsing and retrieval ineffective. The necessity for automated video structure analysis is highlighted by the extent and volume of information found in video databases. Thus, one of the important methods for viewing and retrieving videos is shot boundary detection (SBD). Images with rich information are

***Author for Correspondence**
Ayushi P. Yeram
E-mail: yeramayushi26@gmail.com

[1]Research Scholar, Department of Electronics and Communication Engineering, G H Raisoni University, Amravati, Nimbhora, Maharashtra, India
[2]Associate Professor, Department of Electronics and Communication Engineering, G H Raisoni University, Amravati, Nimbhora, Maharashtra, India

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used in content based video indexing and retrieval since SBD seeks to identify transitions and the boundaries between successive images.

A video shot is a collection of uninterrupted visual sequences continuously captured by a single camera. Videos are basically hierarchical in structure. Meaningful scenes are created by combining video shots, and a compilation of these scenes is called a video (Figure 1). The distance between two shots is known as a shot boundary. A video shot transition can be of two main types i.e. Abrupt (Cut) and Gradual. Gradual transitions are further classified into Fade in/out, Dissolve and Wipe.

1. *Abrupt or Cut:* This kind of shot boundary occurs when one shot suddenly transitions into another. When the final frame of one shot is followed by the opening frame of the subsequent shot, this is known as a shot cut.
2. *Fade:* The image's frames progressively transition to or from black.
3. *Dissolve:* The first shot's frames are progressively transformed into the second shot's frames.
4. *Wipe:* The first shot's frames are progressively transferred into the second shot's frames, either vertically or horizontally.

Compared to a gradual transitions, it is very simple to distinguish between an abrupt or hard transitions because of the fact that gradual transition (GT) incorporates a number of unique editing effects. Furthermore, motions of the camera, lights, and objects can provide incorrect results for the detection of shots.

The shot boundary detection process described in Figure 2 includes segmenting the video into many frames, preprocessing which includes feature extraction, similarity matching or creation of continuity function and finally determining the shot boundary. It can also be categorized as either abrupt or gradual. The frames needed for preprocessing are provided by the video segmentation. Feature extraction is part of the preprocessing step. A number of feature descriptors are accessible, and they can be in RGB, HSV, or LAB formats. Each of the aforementioned characteristics has pros and cons of its own. One or more descriptors can be used for preprocessing, depending on the particular histogram.

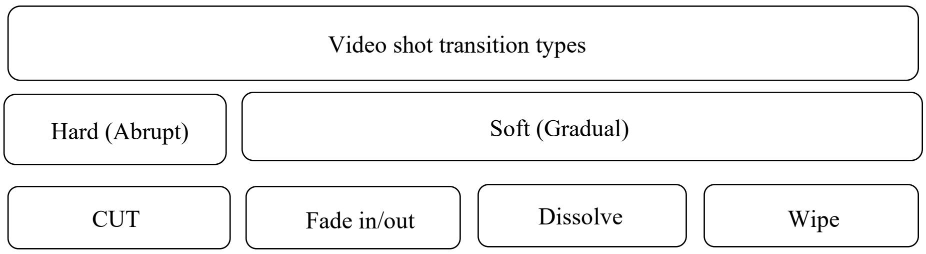


**Figure 1.** Types of videos shot transitions.

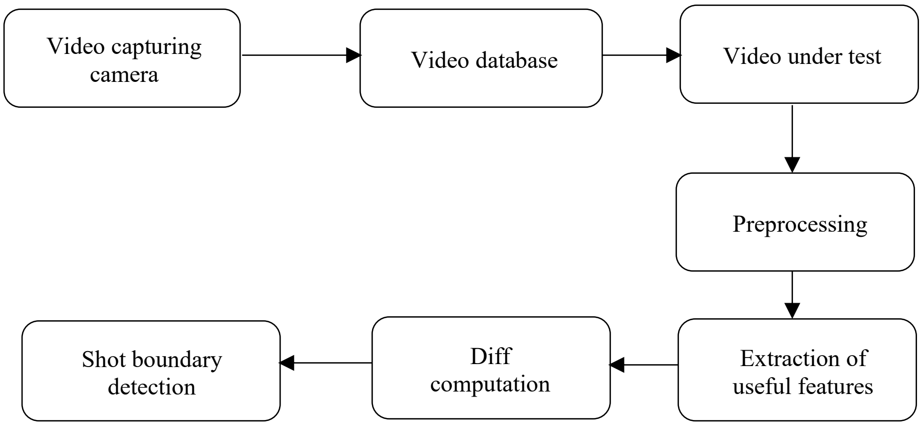


**Figure 2.** Steps in SBD.

 

Walsh Hadamard Transform, Fuzzy Logics, Convolutional Neural Network, High Level Fuzzy PetriNet, and other techniques helped to achieve the impressive results with reference to literature on video processing research, particularly in shot boundary detection. Each of the aforementioned factors contributes to a high Precision and Recall score; as a result, the F1 Score, which is a combined value, aids in evaluating the methodology. As may be observed in detail, there are compromises made between user-oriented and complex approaches, execution speed and accuracy, etc.

The datasets that are used to test SBD algorithms are important and need to be carefully chosen and examined. Because researcher datasets are constrained by availability, representativeness, and ground truth availability, standard datasets are suitable for review. Furthermore, researchers' datasets are not always accessible. Sometimes domain or website problems cause these datasets to be inaccessible. Results may be skewed since not all datasets are representative and cover all transition types that need to be assessed. Since ground truths are not linked to researchers' datasets, other researchers find it challenging and time-consuming to construct these datasets.

The National Institute of Standards and Technology co-sponsors the TRECVID review. TRECVID was founded to analyze and benchmark SBD tasks, and it has helped to enhance SBD algorithms. The most well-known datasets of TRECVID for SBD are TRECVID 2001, TRECVID 2005, TRECVID 2006, and TRECVID 2007. The institute provides these datasets for free after submitting a designated application form. Specifically, the TRECVID 2001 dataset contains hard, dissolve, and fade transitions. TRECVID 2007 is primarily developed for abrupt transitions. The TRECVID 2005 and 2006 datasets are regarded the most difficult because to the variety of their transitions. Also, RAI dataset, some random movie clips, TV and News shots created with Adobe Premiere 4.2.1, Video data from digitalized TV programs are also used for some research papers.

## REVIEW OF LITERATURE

The video shot boundary is a fundamental aspect of video processing research for various purposes. With regard to this, several approaches were used to implement the transitions indicated here. Kalaivani and Anusuya proposed a novel symmetry shot boundary detection system that maximizes detection accuracy by analyzing a video's transition behavior and segmenting it initially into primary and candidate segments using the color feature and the local adaptive threshold of each segment [1]. The cut and gradual transitions are then fine-tuned from the candidate segment using Speeded-Up Robust Features (SURF) derived from the boundary frames, which reduces computational complexity.

The research by Li *et al*. provides a shot boundary identification system that uses both global and target features. The RGB color histogram features from the video frame are extracted. Then, using GMM, recognize foreground objects in video frames and extract their SIFT features. When compared to other algorithms, the feature fusion algorithm's recall and accuracy have improved, and it has resolved the issue of ignoring the target features. The drawback is that the algorithm will detect a certain video more effectively [2]. Tippaya *et al*. used a multi-modal visual features-based SBD framework to evaluate visual representation behaviors using discontinuity signals. A candidate segment selection method is chosen that does not need a threshold computation. Instead, they use the cumulative moving average of the discontinuity signal to identify shot boundaries and skip non-boundary frames. Transition detection distinguishes between cut and progressive transitions, such as fade-in/out and logo occurrence [3].

Priya and Domnic introduced a WHT method for the SBD in which the WHT kernel matrix was used to extract the features of edge, color, texture, and motion. As a result, matching can be examined for different extracted video frames, and the continuity function can then be used to design the system that determines the boundary detection [4]. GG and Domnic has given a novel approach to identify shot boundaries in video sequences by employing orthogonal vectors to extract edge strength from frame blocks [5]. Additionally, a transition recognition method is also provided that can recognize shot and non-shot borders in video clips.

 

Machine learning approach is mostly used to classify the transitions in shot and non-shot categories. SVM is the most preferred classifier for this purpose. Idan *et al*. used the Squared Tchebichef-Krawtchouk polynomial (STKP) for feature extraction with SVM as classifier with the disadvantage that this method is used only for cut transitions [6]. Separate detection algorithms have also been constructed using convolutional neural networks, taking into account the types of transitions as abrupt and gradual [7]. In order to classify clips into distinct shot change types, abrupt transitions are detected using a combination of color histogram and deep features, whereas gradual transitions are discovered using 3D CNN.

Fuzzy logic is another approach used by Thounaojam *et al.* which used fuzzy system as a classifier for abrupt and gradual transition detection with the use of genetic algorithm (GA) as an optimizer [8]. This method is advantageous in computational time but lacks accuracy as shot boundaries increase with rise in GA optimization. Dadashi and Kanan also used fuzzy rule-based approach for automatic cut transition detection in which no threshold or other parameter is used [9].

Chakraborty *et al*. proposed wipe scene detection method which used the linear regression and inflated 3D-convolutional neural network (I3DCNN) [10]. The suggested approach performs better than current wipe scene change detection techniques in terms of quick processing and a variety of object-camera motion-based wipe transition identification tasks. Feature fusion and clustering technique is used by Duan and Meng which combined SURF and fingerprint features, and K-means is used to cluster the fused features [11]. The experimental findings demonstrate the excellent accuracy and time efficiency of the suggested approach, particularly for long shot detection and gradual shot boundaries. Yuan *et al*. proposed dynamic mode decomposition (DMD) based video shot detection which was called as universal method for shot transitions like hard cuts fades and dissolves [12]. It is determined whether the video's content is connected by obtaining the amplitude of the temporal background mode from the modes that DMD extracted. The amplitude of the temporal background mode abruptly varies if the content is from distinct shoots, allowing us to determine the shot boundaries. In the meanwhile, the approach successfully lowered the rate of error shot boundary identification when the foreground object (or camera) moved more quickly or when the illumination changed dramatically.

Kirsh directional derivative based shot boundary detection is used by Shekar and Uma in which Kirsh operator gave accurate edge localization property for feature extraction which provided accuracy and efficiency to the work [13]. Li *et al*. used sparse coding technique for detecting shot boundary which explored dictionary learning for keyframe selection and video summarization [14]. Singular value decomposition (SVD) is another accurate method for detecting hard and gradual shots given by Youssef *et al.* which used different mathematical interpretations and theorems [15]. Hannane *et al*. proposed SIFT point distribution histogram method which is novel, fast and detects shot boundaries for different levels of illumination, camera operations including zoom in, zoom out, camera rotation and motion effects [16]. Kar and Kanungo suggested a cut detection method using weber features, which performed well in light environments but produced erroneous matches in dark ones [17].

## METHODOLOGY

As noted in the literature study, numerous efficient strategies have been created for abrupt as well as gradual (fade in/out, wipes and dissolves) type of transitions. The comparative analysis focuses on detection of gradual type of transitions in terms of accuracy, computation speed, and simple/complexity techniques. Video frame extraction and segmentation are the initial steps in the general procedure. Next, preprocessing consists of extraction of features. Similarity calculation is to be done and then the shot boundary is detected.

Literature reviewed here presented different methods and algorithms to detect the gradual type of transitions like Sasisthradevi and Roomi provided multi-boundary classification (Grouped gradual transitions, cut transitions and no transitions) with the help of new pyramidal opponent color shape model and bagged tree classifier but on other side wipe analysis was insufficient [18]. Color based histogram and SURF feature descriptor based study investigated gradual transitions but lacked to identify the particular type of that transition [1]. Multimodal visual features based method gave good performance to identify cut and gradual transitions (fade in/out, logo occurrence) but sensitive to camera object motion [3]. Prabavathy and Devi proposed fuzzy rule and histogram difference based system which calculated number of dissolves and wipes [19].

Shen *et al*. proposed HLFPN model based on matching learning, SURF key-point matching and histogram difference for gradual transitions which removed false detections obtained by existing methods but having inconsistent recall value [20]. FFCT is the fast shot boundary detection technique which is based on separable moments and SVM provided with the best accuracy and time efficiency in detection of gradual shot boundary and long shot detection [6]. Chavate *et al*. used integration of WHT and DTCWT for feature extraction and by using this method much accurately detected fade in/out transitions with reduction in false alarms [21].

The recall, precision, and F1 score are introduced as evaluation metrics in accordance with the relevant shot boundary detection investigations in order to confirm the efficacy of the suggested method. These parameters are specified by:

$$\text{Precision (P)} = \frac{\text{No.of correct transitions reported}}{\text{Total no.of trasitions reported}} \times 100$$

$$\text{Recall(R)} = \frac{\text{No.of correct transitions reported}}{\text{Total no.of transitions in reference}} \times 100$$

$$\text{F1 Score} = \frac{2.P.R}{(P+R)}$$

The research outcomes of this work are that it gives a comprehensive statistical comparison of all gradual transition kinds in one location. Recent research has mostly concentrated on wipe and dissolve types of gradual transitions in order to improve them in terms of lighting effects, camera motions, and so on. Thus, the primary focus of this study is on the overall statistical performance of both wipe and dissolve types of video transitions, as well as the comparison of datasets used to analyze them [22, 23].

## RESULTS AND ANALYSIS

There are different gradual transition detection methods having been compared which used TRECVID datasets and shown in Table 1 in terms of above performance determining parameters and Figure 3 shows the statistical analysis for the same.

A velocity imbalance is produced in a single frame by wipe transitions, a form of gradual transition, which has a variety of motion pattern modifications when influenced by object-camera motion (camera pan, large-object, and zoom-in/out). Moreover, incorrect detection results from this motion imbalance. Numerous methods have been proposed to identify wipe type of transitions effectively; higher accuracy in wipe no-motion class detection is achieved alone by the pixel-border trajectory-based method [24–26] and histogram feature based [27], but a high temporal feature is required for large object-camera motion. On the other hand, temporal features are extracted by the macroblock and SGOP-based techniques; nevertheless, a satisfactory balance of spatial and temporal features is absent in the case of large-scale object-camera motion [28]. Deep SBD method used 3D-CNN and SVM classifier to detect wipes and also spatial and temporal deep features are evaluated but lacked in processing time [29]. A novel method is proposed by Chakraborty *et al.* based on deep spatial motion feature analysis which detected non-motion, object-camera based motion as well as half wipe pattern effectively with great accuracy [10]. Table 2 compares different approaches to detect wipe transitions and Figure 4 shows statistical analysis for the same.

 

**Table 1.** Performance comparison of different gradual transition detection approaches on TRECVID datasets.

| Label | Method | Precision | Recall | F1 Score | Datasets Used |
|---|---|---|---|---|---|
| M1 | WSCD | 94.9% | 95.3% | 95% | TRECVID 2001 and TRECVID 2007 |
| M2 | TSSBD | 93.20% | 93.80% | 93.50% | TRECVID 2005 |
| M3 | VSBD-POCS | 91.9% | 88.5% | 90.4% | TRECVID 2001, TRECVID 2007 and VIDEOSEG2004 |
| M4 | WHT | 88% | 85% | 86.6% | TRECVID 2007 |
| M5 | Best TRECVID Performer [30] | 79.1% | 78.8% | 79.0% | TRECVID 2005 |
| M6 | Color-Based Histogram Difference and SURF Feature Descriptor | 91.7% | 92.6% | 92.1% | TRECVID 2001 |
| M7 | Multimodal Visual Features Method | 78.3% | 76.3% | 76.8% | TRECVID 2001 |
| M8 | Visual Color Information Method | 85.2% | 88% | 86.5% | TRECVID 2001 and 2007 |
| M9 | SVD and Pattern matching | 83.3% | 81.0% | 81.5% | TRECVID 2001 |
| M10 | GA and Fuzzy Logic | 86.4% | 78.5% | 82.2% | TRECVID 2001 |
| M11 | DMD | 91.6% | 85.6% | 88.5% | Videos from movies and movie trailers |
| M12 | Histogram Difference and Fuzzy rule | 98% | 98% | 99.5% | TRECVID 2006 |
| M13 | FFCT [6] | 92.05% | 97.62% | 94.75% | TRECVID 2001, 2005, 2006 and 2007 |
| M14 | HLFPN-KM [20] | 91.86% | 96.89% | 94.31% | 10 various types of video clips including movie, music video, commercial video, TV shows, etc. |
| M15 | ORB-SSIM | 91.34% | 91.88% | 91.61% | Open video project and RAI |
| M16 | PSOGSA | 91.23% | 97.53% | 94.27% | TRECVID 2001 |
| M17 | WHT+DTCWT [21] | 90.5% | 91% | 91% | TRECVID (2016-2019) |

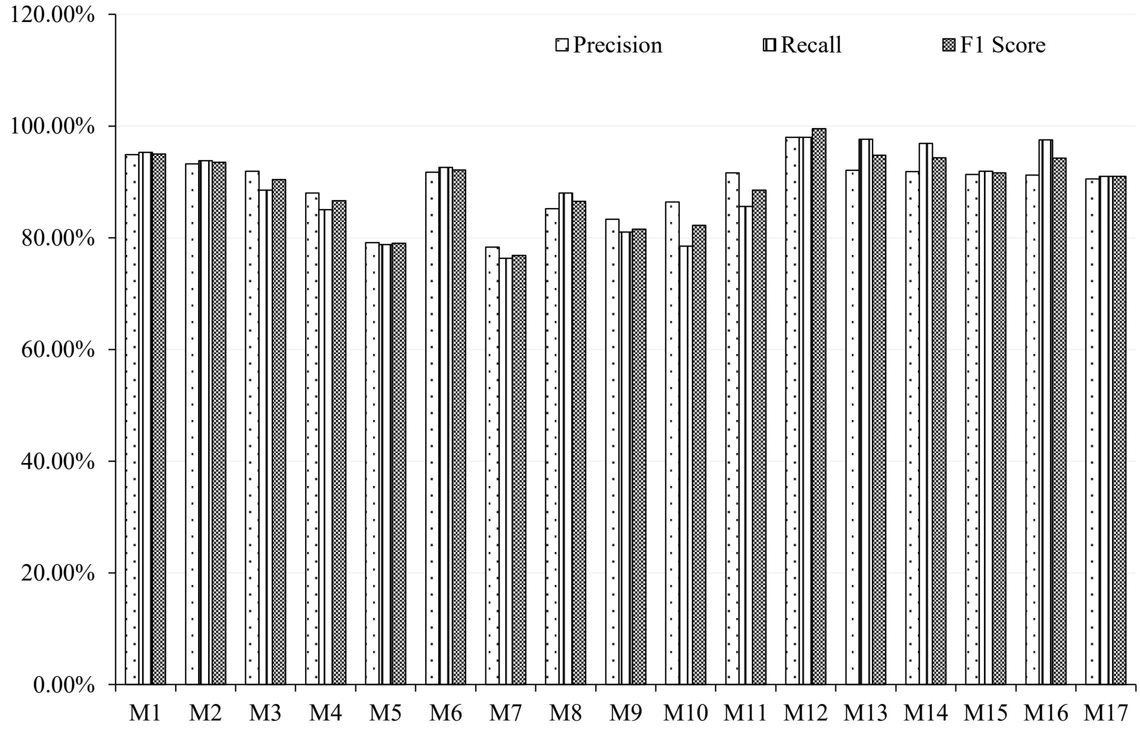


**Figure 3.** Statistical performance comparison for gradual transition detection methods.

 

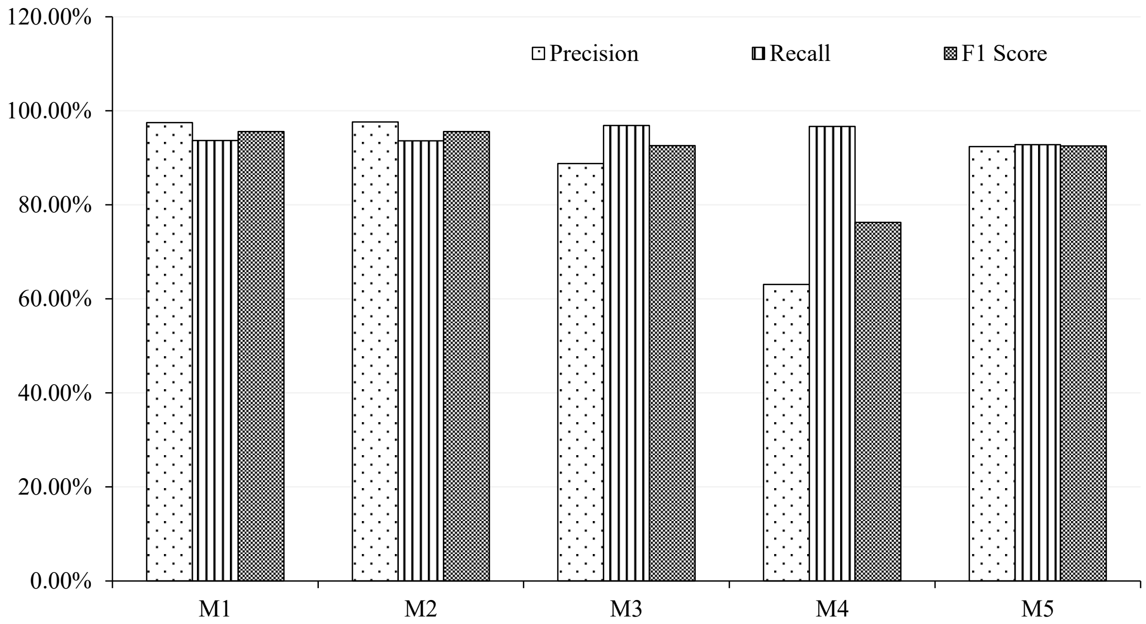


**Figure 4.** Statistical analysis of wipe transition detection method.

**Table 2.** Performance comparison of different approaches for wipe detection.

| Label | Method | Precision | Recall | F1 Score | Datasets Used |
|---|---|---|---|---|---|
| M1 | WSCD [10] | 97.5% | 93.7% | 95.6% | TRECVID 2001 and 2007 |
| M2 | Deep SBD [29] | 97.6% | 93.6% | 95.6% | TRECVID 2001-2007 |
| M3 | MG+SGOP [28] | 88.8% | 96.9% | 92.6% | |
| M4 | Histogram space [27] | 63.1% | 96.7% | 76.3% | TV and News shots created with Adobe Premiere 4.2.1 |
| M5 | Pixel border based [24] | 92.4% | 92.8% | 92.5% | Video data from digitalized TV programs and TRECVID 2005 |

**Table 3.** Performance comparison of different approaches for dissolve transition detection.

| Label | Method | Precision | Recall | F1 Score | Datasets Used |
|---|---|---|---|---|---|
| M1 | TSSBD [7] | - | - | 89.4% | TRECVID 2005 |
| M2 | WHT [5] | 85.4% | 87.5% | 86% | TRECVID 2007 |
| M3 | Twin comparison method [31] | 70.42% | 64.94% | 67.57% | - |
| M4 | Color Histogram [26] | 95.04% | 93.92% | 94.26% | Five videos from different movies |

Detecting dissolve transitions is more challenging than detecting fade in/out and wipe transitions. During this transition, the previous shot's last frames fade out and the next shot's first frames fade in, resulting in an overlap of fade out and fade in. Dissolves may consist of three or more frames. In certain videos, dissolves can be as short as three frames. Detecting dissolves has significant hurdles. Illumination and camera/object motion can lead to false positives, thus impacting algorithm performance. When the camera follows the object, the suggested algorithm based on color histogram difference successfully removes disruptions brought on by changes in illumination and rapid motion but this approach is sensitive to uncommon situations where the background in successive frames rapidly changes in addition to several things in the same image appearing and disappearing [26, 30–33]. TSSBD used C3D based deep analysis for dissolve detection and the results are more accurate as compared to others [7]. Despite numerous attempts, researchers were unable to ensure resilience in the presence of illumination and object/camera motion. Therefore, this issue needs to be addressed. Table 3 shows some performance comparison for dissolve transition methods and Figure 5 shows the statistical analysis for the same.

 

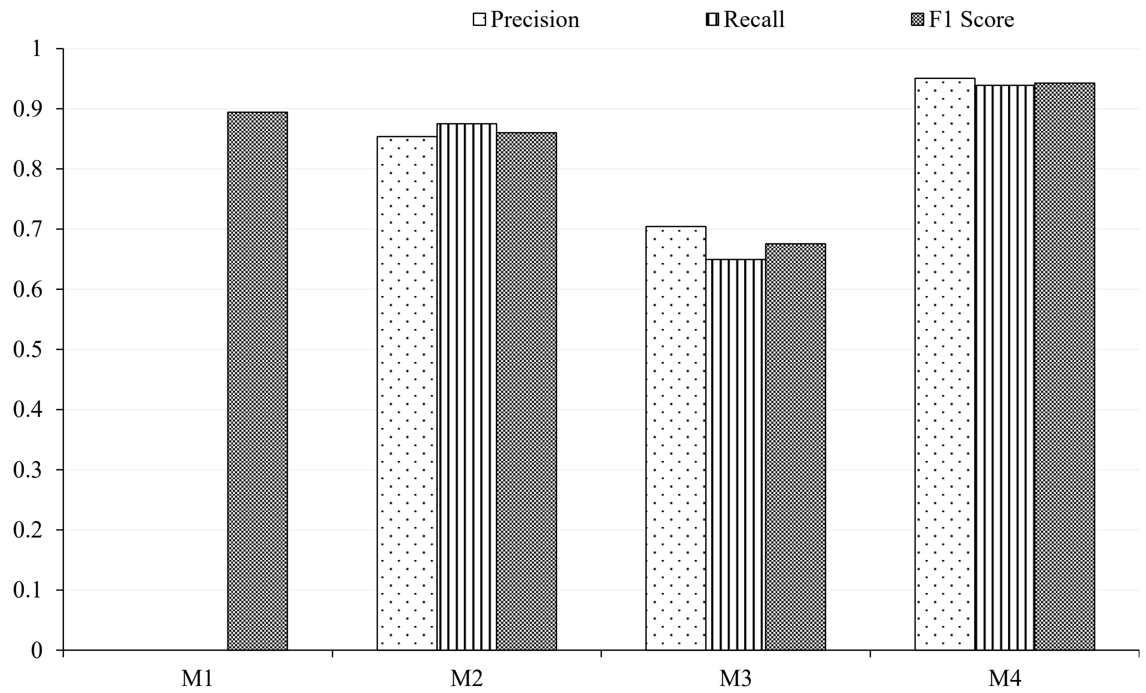


**Figure 5.** Statistical analysis of dissolve transition detection methods.

## CONCLUSION

This study focuses on many approaches used for both abrupt and gradual type shot boundary detection. This review discusses various methodologies that were able to identify gradual changes. The study mainly reviews about the methodologies and challenges came into picture for detecting wipe and dissolve type of gradual transitions.

It compares the various wipe and dissolve transition detection methods in terms of F1 score, precision, recall and the use of datasets at same place which will be useful for researchers for further advancement in the research study of gradual transitions with new algorithms.


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