Indonesian Journal of Electrical Engineering and Computer Science
Vol. 39, No. 3, September 2025, pp. 1955~1963
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v39.i3.pp1955-1963

Texture-based two-stage shot boundary detection in videos

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Article Info

Article history:

Received Sep 10, 2024
Revised Apr 16, 2025
Accepted Jul 3, 2025

Keywords:

Euclidean distance
Histogram computation
Local quad pattern
Shot boundary detection
Texture feature extraction
Video analysis

ABSTRACT

In recent years, shot boundary detection (SBD) has become an essential component of video processing, enabling applications such as video indexing, summarization, and content retrieval. However, the task remains challenging due to frequent false positive detections caused by illumination variations, motion changes, and diverse editing effects. To address these challenges, this paper presents a novel two-stage SBD framework that leverages local quad pattern (LQP) histogram features for precise transition detection. In the first stage, histogram feature vectors are derived by counting the occurrences of LQP codes (−1, +1, 1, 0), and abrupt transitions are identified using the Euclidean distance between consecutive frames. In the second stage, mean values of each histogram bin are computed for consecutive frames, and a similar distance-based approach is applied to refine detection accuracy. A transition frame is confirmed as a shot boundary only if both stages detect it, thereby reducing false positives. The proposed method is evaluated on the TRECVid 2001 and 2007 benchmark datasets, and experimental results demonstrate its superior performance compared to existing algorithms.

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1. INTRODUCTION

The exponential growth of social media and online video platforms has led to a surge in multimedia content generation, making efficient video data management a critical challenge. The user cannot easily manage and retrieve digital data because of the raw video data having naturally unstructured format. To make the structural characteristics for streaming raw video data to effectively handle the video data for many processes such as video summarization, scene understanding, indexing, and retrieval, the content-based video retrieval system is needed. A video is a continuous frame sequence which consists of significant intra-relevant frames that are defined as shots. A shot is defined as a series of frames in a video by a specific sequential range with correlated information. The activity of extracting the margin between every two sequential range frame sequences is called shot boundary detection (SBD).

A video is a continuous frame sequence that consists of significant intra-relevant frames that are defined as shots. A shot is defined as a series of frames in a video by a specific sequential range with correlated information. The activity of extracting the margin between every two sequential range frame sequences is called SBD. The SBD has two types of transitions such as abrupt transition and gradual transitions [1], [2], caused by various editing effects like fades, dissolves, and wipes. Accurate SBD is essential for video analysis, but existing methods face significant challenges [3], [4].

Despite the progress in SBD techniques, many existing methods struggle with challenges such as sudden illumination changes, dynamic camera motions, and complex object movements, leading to false positives and reduced accuracy. Traditional approaches, such as histogram feature representation and edge-based methods [5]–[7], offer low computational cost but often fail to handle these complexities effectively. Even advanced methods using machine learning, deep learning, and texture descriptors like local binary patterns (LBP) and local ternary patterns (LTP) have limitations in specific scenarios, particularly in maintaining robustness against illumination and motion variations.

The need for a more accurate and robust SBD method that can effectively handle the complexities of modern video content, including abrupt transitions and dynamic changes, drives the development of this research. Enhancing the accuracy of SBD is crucial for improving video analysis tasks like summarization, retrieval, and scene understanding.

To address these challenges, this paper proposes a novel two-stage shot boundary detection TSSBD technique. The primary objective of the TSSBD is to detect shots in video frame sequences by identifying abrupt transition effects through a two-stage process. The proposed method leverages texture feature extraction and histogram computation to improve detection accuracy and reduce false positives, especially in challenging scenarios involving illumination changes, dynamic camera motions, and complex object interactions. The main contributions of this paper are as follows:

- Proposing an LQP-based texture analysis approach that improves transition detection in challenging video sequences.
- Developing a two-stage verification method that reduces false positives and enhances detection robustness.
- Demonstrating that TSSBD outperforms on benchmark datasets (TRECVid 2001 & 2007), making it applicable to real-world video segmentation tasks.

2. RELATED WORKS

This section reviews various shot boundary detection (SBD) methods and outlines the general workflow commonly adopted in this domain. Typically, an SBD process is divided into three main phases: (1) feature extraction, where representative characteristics such as color, texture, or motion are obtained from video frames; (2) continuation signal derivation, in which temporal variations of the extracted features are analyzed to generate a sequence of similarity or dissimilarity measures between consecutive frames; and (3) transition identification, where abrupt or gradual shot boundaries are detected based on significant changes in the continuation signals.

2.1. Feature extraction

The features can be extracted from frame sequences that are used to efficiently represent the visual information of the frame sequence. Several types of features are introduced in the video and image processing research work. The features can be categorized such as pixel occurrence-based, histogram representation-based, edge computation-based, and transform-based. The pixel occurrence-based technique is a simple approach to detect shot boundary) [8]–[10]. In this work, the pixel intensities are directly extracted without any processing to represent visual information. Though the pixel occurrence-based method is very efficient, it is very sensitive to camera motion and objects with high speed. This motion sensitivity directly affects SBD accuracy. Therefore, the precision rate is automatically reduced due to the false alarm rate increased [11], [12].

2.2. Histogram representation-based techniques

To mitigate the sensitivity of pixel occurrence-based methods, histogram representation techniques were introduced [13], [14]. The histogram representation is highly dependent on the spatial information on each frame by deeming the intensity or color or texture distribution. The spatial dependency makes the sensitivity in local and global motions in histogram representation technique. The histogram technique is applied on the various types of color distribution [15] respectively, gray scale color, RGB, HSV, and l*a*b. However, histogram representation-based techniques are less sensitive to object motion and camera motion compared to pixel occurrence-based techniques.

2.3. Edge computation technique

Edge features are extracted to reduce the influence of background information [16] and camera motion as well as flashlight effects. Yoo *et al*. [17] developed an edge based object tracking method to detect shots in a frame sequence. This work computes the ratio of edges between exiting and entering edges in the consecutive frames that are used to detect shot transitions [18], [19]. Though edge computation-based techniques get the advantage of edge computation as a frame feature, the SBD detection accuracy is still less due to edge computation-based techniques being expensive where the number of processes employed to detect edges, their performance is less compared to histogram representation based technique. Edge computation-based technique well worked in case of flash light occurs since edges are invariant to illumination change in the frame sequence.

2.4. Transform based techniques

This technique has been utilized frequently for transition detection in recent years. Porter *et al.* [20], used the technique to find the correlation between transform coefficients in the blocks of a frame as features to detect transition effects. Priya *et al*. [21], developed an algorithm for SBD using the WlashHadamard transform, this technique extracted features for the small block. Non-Subsampled Contourlet Transform is applied to extract the features from the low-frequency sub-band for each CIE l*a*b* color space for SBD. Though the methods such as [22], [23] achieved high accuracy, the computational cost was high.

The observations are made on literature review as follows: the sudden illumination changes and camera motion changes are the factors obstacle in abrupt transition detection. The result in SBD is inaccurate when the multiple transition effects occur in a frame simultaneously. To overcome the above challenge, this paper introduced the TSSBDtechnique using texture feature extraction and histogram computation methods.

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3. THE TSSBD APPROACH

This section explains the proposed TSSBD approach and the flow chat of the proposed work is explained in Figure 1. The primary objective of this research is to develop a novel TSSBD technique that leverages local quaternary pattern (LQP)-based texture feature extraction to enhance the detection of abrupt transition effects in video sequences. This approach aims to address the shortcomings of existing SBD techniques by improving transition detection accuracy and robustness. The proposed work consists of four steps namely gray scale conversion as a pre-processing stage, LQP texture feature extraction, similarity analysis, and SBD identification.

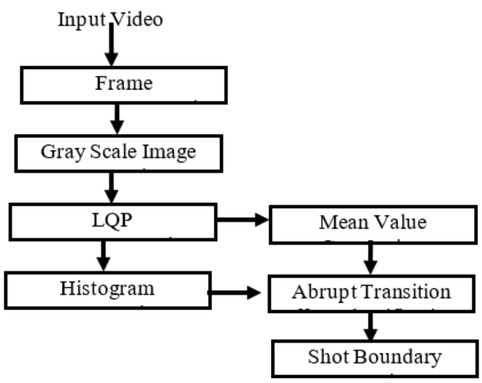

Figure 1. Work flow of the proposed TSSBD

3.1. Pre-processing

The gray scale conversion is a pre-processing stage as the first step in the TSSBD proposed approach. The TSSBD considers the input as a color frame sequence. However, the RGB colors are very sensitive from light scattering or reflection, color video frames. Therefore, color frame sequence needs to be converted into gray scale images using [24] the (1).

$$P = \frac{P_R+P_G+P_B}{3} \tag{1}$$

where P is the color pixels where P_R, P_G, and P_B are the red, green and blue color channels of RGB respectively.

3.2. LQP feature extraction

In general, texture-based classification or prediction is primarily used to differentiate frame sequences based on their objects. Texture features effectively describe the nature of the content in an image or video. In most video analysis tasks, local binary pattern (LBP) is widely used for texture classification, as it performs well against intensity variations even in the absence of significant gray-level differences. However, research [25] has found that LBP features are highly sensitive to noise. To address this limitation, local ternary pattern (LTP) was introduced [25]. While LTP effectively detects abrupt transitions, its overall F1-score is reduced due to a trade-off between recall and precision recall is compromised while precision improves. To further enhance abrupt transition detection and achieve a better F1-score, LQP is introduced. LQP follows a new pattern in which the center pixel encodes four values (-1, +1, ++1, 0) based on neighboring pixel intensities. The threshold values t1 and t2 are user-defined and applied to the grayscale image to distinguish meaningful texture variations from noise. The LQP framework is illustrated in Figure 2. The threshold values are applied on the gray scale image and the LQP is described in Figure 2.

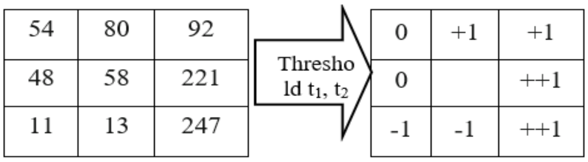

Figure 2. Illustration of the LQP

let g_c be the center of the pixel and let g_n be the neighbourhood pixels where g_n $(n = 0, ..., n - 1)$. The circle is made incorporating all respective neighbouring pixels that are denoted as R and N to define for counting the neighbouring pixels using bilinear interpolation computation in (2).

$$LQP_{RN} = \sum_{n=0}^{n-1} 2^N k(g_c - g_n), \tag{2}$$

where k is the neighbour pixel values after applying the threshold values t_1 and t_2 in (3).

$$s(k) = \begin{cases} 0, if\ g_c + t_1 \geq k \geq g_c - t_1 \\ +1 \quad if\ k \geq g_c - t_1 \\ ++1 \quad if\ k \geq g_c - t_1 \\ -1 \quad otherwise \end{cases} \tag{3}$$

3.3. First stage abrupt transition identification

3.3.1. Histogram computation

To identify the shot in the frame sequence for the first stage, a histogram feature vector is derived by counting the occurrence of LQP four values. This histogram features vector has the potential ability to differentiate the spatial activity in a frame. This histogram vector consists of four bins where each bin consists of occurrences of counting the number of 0, −1, +1, and ++1.

Let f_i be the frame number where $i = 1$ to N and h_j be the histogram feature vector where $j = 1$ to n. Based on the respective histogram feature vector, the transition of the frame sequence is identified by using Euclidean distance measure [26] between consecutive frames h_j, it is explained in the (4).

$$\text{Distance}\ (h_j) = \sqrt{\sum_{j=1}^{n}(h1_i - h2_i)^2} \tag{4}$$

where h_1 and $h_2$are the elements of consecutive histogram feature vector. A threshold value is applied on the h_1 and $h_2$to identify the transition effects.

3.4. Second stage abrupt transition identification

3.4.1. Mean conversion

To identify the transition in the frame sequence for the second stage, mean value (m_r) is to be computed from each histogram bin *(–1, +1, 1, 0)* where $r = 1$ to m. Let*a, b, c,* and *d*are the total codes of *–1, +1, 1, 0*respectively. The $m_r$is to be computed by using the (5).

$$m_r = \frac{a}{n},\ \frac{b}{n},\ \frac{c}{n},\ \text{and}\ \ \frac{d}{n} \tag{5}$$

where$n$ is the total number of occurrence of codes. Based on the m_r of each code of the consecutive frames, the transition of the frame sequence is identifiedusing the (6).

$$Dis\,tan\,ce\,(m_r\,, m_{r+1}) = \sqrt{\sum_{r=1}^{n}(m1_s\, - m2_s)^2} \tag{6}$$

wherem_1 and m_2 are the mean values in the consecutive frame and s is the corresponding code elements. The distance between $m_r$and $m_{r+1}$is computed for all four codes.

3.4.2. Shot boundary detection

If the distance between m_r and m_{r+1} increases or decreases drastically compared to the previous frame, it is identified as a transition frame. For efficient SBD, shots are identified using both histogram computation *(h_j)* and mean computation *(m_r)*. If TSSBD detects the same transition frame for both *(h_j)* and *(m_r)*, that frame can be considered a shot boundary.

4. EXPERIMENTAL RESULTS

The TSSBD approach is experimented using the MATLAB tool to evaluate the experimental results. The TRECVid 2001 and 2007 video dataset are applied to evaluate the effectiveness of the TSSBD approach. The TRECVid 2001 and 2007 consist of movie clips which are the challenging subject to motion effect, lighting effect, illumination changes, etc. Both datasets provide ground truth annotations for evaluating detection accuracy and are ideal for testing the robustness of video segmentation methods due to their diverse content and real-world challenges. The description of overall selected videos is explained in Table 1.

Table 1. Ground truth data of the test video data

Source	Video	Frames	Transition effect
TRECVid 2001	D2	16586	42
	D3	12304	39
	D4	31389	98
	D5	12508	45
	D6	13648	40
TRECVid 2007	BG_3027	49815	127
	BG_3097	44991	91
	BG_3314	35802	44
	BG_16336	2466	127
	BG_28476	23238	176
	BG_36136	29436	88
	BG_37309	9639	11
	BG_37770	15836	8
Mission impossible transformer movie song	ClipMI	3444	63
	ClipTI	7721	38
	Massom	9193	41

4.1. Performance metric

This paper used the following measures for evaluating the results: F1 score, precision, and recall. These are explained by the following in (7), (8), and (9).

$$Precision = \frac{\text{TP}}{\text{TP} + \text{FP}}, \tag{7}$$

$$Recall = \frac{\text{TP}}{\text{TP + FN}}, \tag{8}$$

$$F1-score = 2 \times \frac{Pr\,ecision \times \text{Recall}}{Pr\,ecesion+Re\,call}, \quad (9)$$

where true positive (TP) correctly detected the shot, false positive (FP) incorrectly detected the shot, and false negative (FN) detected the wrong shot as correct shot. The proposed experimental results are explained in Table 2.

Table 2 Performance of proposedTSSBD approach

Sl. No.	Video	Precession	Recall	F1-Sore
1	D2	98.02	91.50	94.73%
2	D3	98.09	92.64	95.28%
3.	BG_3027	97.06	98.07	97.56%
4.	BG_3097	96.12	97.07	96.59%
5.	ClipMI	98.47	92.08	95.16%

4.2. Comparative analysis

To evaluate the effectiveness of the proposed work, the existing SBD algorithms are compared with the proposed approach. The existing algorithms such as canny detection, neural network, and bifold stage SBD using D2 and D3 video clips. The comparison results are shown in the Table 3. Figure 3 illustrates the shot transitions in a video sequence, highlighting abrupt changes between shots 1, 2, 3, and 4, with corresponding transition frames between each shot.

Table 3. Comparative analysis

Algorithm	F1-score	
	D2	D3
Canny detection	95.00%	92.00%
Neural network	91.40%	89.60%
Bifold stage SBD	93.80%	90.10%
Proposed approach	94.73%	98.28%

Figure 3. SBD using the proposed method, highlighting abrupt transition frames

4.3. Discussions

This study proposed a two-stage TSSBD method based on LQP to improve the accuracy of detecting abrupt transitions in video sequences. Our results show that TSSBD outperforms existing methods, particularly in handling illumination variations, motion changes, and occlusions in video datasets. The TSSBD method achieved higher F1-scores compared to traditional SBD techniques such as Canny detection, neural networks, and bifold-stage SBD. For example, the proposed method achieved an F1-score of 98.28% for video D3, compared to 92.00% for Canny detection and 89.60% for neural networks. This indicates that the combination of LQP feature extraction and two-stage verification significantly enhances SBD accuracy.

Additionally, the proposed method effectively reduces false positives, ensuring that detected transitions are actual shot boundaries rather than artifacts from lighting changes or motion effects. However, a small number of false detections still occurred in frames with non-uniform illumination, which suggests the need for further refinement in handling complex lighting conditions. Tables 1,2,3 and Figure 2 present the best results achieved by the TSSBD approach. For the experiments, videos D2, D3, D4, D5, and D6 from TRECVid 2001 and BG_3027, BG_3097, BG_3314, BG_16336, and BG_28476 from TRECVid 2007 were randomly selected. Among them, D2 and D3 were specifically chosen to compare the TSSBD approach with existing methods, as these videos contain diverse challenges such as lighting variations, motion changes, and illumination effects. While the proposed method accurately detected shot boundaries at appropriate locations, a few false shot detections occurred in frames with uniform and non-uniform illumination effects due to insufficient transitions in the frame sequence. Examples of these illumination effect frames are shown in Figure 3.

Prior studies have demonstrated that LBP and LTP provide robust texture descriptors but suffer from sensitivity to noise and trade-offs between recall and precision. Unlike LBP and LTP, LQP introduces a four-level encoding scheme, allowing for more detailed texture representation and reducing the impact of illumination variations. Moreover, previous deep learning-based SBD methods have shown high accuracy but require extensive computational resources. In contrast, our approach achieves competitive accuracy while being computationally efficient, making it suitable for real-time video analysis applications.

5. CONCLUSION

This paper introduced a novel SBD algorithm, TSSBD, for efficiently detecting abrupt transitions. The challenging TRECVid 2001 and 2007 datasets were used to evaluate the proposed approach. TSSBD was developed using LQP feature extraction and histogram techniques. While the two-stage SBD algorithm accurately detected abrupt transitions in most cases, some false shot detections were observed. In the future, the proposed algorithm can be extended to detect both gradual and abrupt transition effects, further enhancing its robustness.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Suma Christal Mary Sundararajan							✓			✓		✓		
Ezhil R		✓				✓				✓				✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Author states no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in https://trecvid.nist.gov/trecvid.data.html.

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