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An Efficient and Robust Temporal Video Segmentation

Jasmin T. Jose, Rajkumar S.

Abstract*: *Temporal video segmentation is the primary step of content based video retrieval. The whole processes of video management are coming under the focus of content based video retrieval, which includes, video indexing, video retrieval, and video summarization etc. In this paper, we proposed a computationally efficient and discriminating shot boundary detection method, which uses a local feature descriptor named local Contrast and Ordering (LCO) for feature extraction. The results of the experiments, which are conducted on the video dataset TRECVid, analyzed and compared with some existing shot boundary detection methods. The proposed method has given a promising result, even in the cases of illumination changes, rotated images etc.

Keywords: Shot Boundary Detection, Video retrieval, LCO, Abrupt Transition, Local descriptor

I. INTRODUCTION

The superabundant use of internet and mobile phones causes the bountifulness of video repository. As this becomes bountiful, the analysis and management of video, become a laborious task. All these tasks on video data together called Content Based Video Retrieval (CBVR). Since shot is the basic building element of a video, the elementary step of this CBVR is shot boundary detection or video shot segmentation. A shot is a group of continual frames of video, which is captured by a camera uninterruptedly. The general structure of a video is shown in Fig. 1. An inevitable step for managing the large video databases is video segmentation. Temporal video segmentation is the process of dividing the video into different shots, which is manageable in size and properties. The SBD is a part of video segmentation, by which, we are trying to find the particular position, where a shot transition is taken place in the input video. In other words, the shot boundary, in which, an end of one shot and the start of next short will exist. The transition is a cut or abrupt transition (AT), if these two boundary frames are consecutive. Fig. 2 Shows a sample frames of cut transition. If the transition is followed throughout a number of frames, then it is gradual transition (GT). This is takes place by the graphical effects which is applied manually to the video. This can be in different forms, wipe, dissolve, fade in/out. To perform the task SBD, we have to consider the basic element of a shot named frames. Each frame of a video is an image, so, as it is composed of a set of features, which are the information relevant for solving the computational task related to a certain application. So the preliminary and prominent step of this SBD is the extraction of features from consecutive frames of input video. Researchers under this promising area of computer vision are using either global or local features or both in their research. Global features represent the image as whole. Whereas, local image features consider the patches of image to describe the image and is more robust in nature. For both global and local features the classifiers also different, as nature of the feature is different.

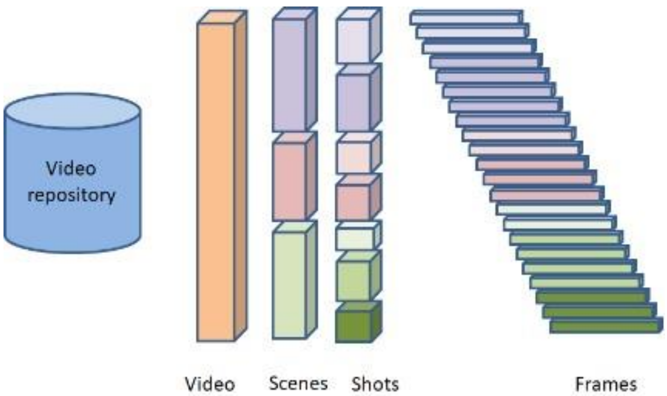

Fig. 1 General structure of a video

Even the computational complexity is high in the case of local features, as it gives more details about the image; researchers are widely using these local features in the area of image matching. Some of them are mentioned here in the literature. Junaid baber et al.[1] presented a framework for video segmentation using entropy as global feature and for fade detection SURF as local feature. They have shown a promising result for video segmentation. Local features can extract maximum details about the image, as it is considering the small parts of image, rather, image as whole in global feature extraction. More number of proposals [2],[3],[4-6], like SIFT, SURF and modifications of these, were come out based on this local features in this area. Conspicuous performance has been given by SIFT [2] descriptor.

So many extensions of this SIFT descriptor is introduced based various applications. PCA-SIFT introduced by [9], used PCA for dimensionality reduction in SIFT descriptor. Enhanced version of SIFT by using log polar location grid, named GLOH (Gradient Location and Orientation Histogram), is recommended by [8].

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* Correspondence Author
Jasmin T. Jose*, Assistant Professor, School of Computer Science and Engineering, Vellore Institute of Technology, Vellore, India. Email: jasminlijo@vit.ac.in
Rajkumar S, Associate Professor, School of Computer Science and Engineering, Vellore Institute of Technology, Vellore, India. Email:rajkumars@vit.ac.in

By the use of integral images the reduced computational complexity descriptor, Speeded Up Robust Feature (SURF) introduced in [5]. ASIFT is another enhanced version of SIFT [10], which deal with the view change in image matching. Singular Value Decomposition (SVD) updating is used with adaptive feature extraction in [11]. In order to identify hard cuts, double thresholding technique is used as classifier. SVD updating for gradual transition detection employed, which warrants the reduction in time complexity. Yoo et al. [12] suggested the variance distribution of edge information as feature for gradual transition detection. By considering a block of frames, the edge strength is extracted using orthogonal vectors by [13]. This approach oversees the effects of fast motion and lighting in the video.

A well founded image matching is done with a new descriptor; Sampling based local descriptor (SLD) in [14]. The sampling is performed using elliptic equations. The method is invariant to the deformations like scaling, rotation, view change etc. but not fully invariant. Matching performance of aforementioned descriptors is good, but, in real time applications, they are inefficient. In order to defeat the problem with illumination changes, rather than the raw intensities of pixels, order of the pixel based feature descriptors [18] were introduced. Due to its discriminative ability, intensity ordering patterns are popular in the area of visual analysis.

Wang et al. [15] suggested a local intensity order pattern (LIOP) to encode the order pattern among the pixels located at a fixed radious. Another order based descriptor, named, interleaved order based local descriptor (IOLD) is recommended by Dubey et al. [16]. In this, a set of interleaved local neighbours of each pixel is considered for creating the descriptor. The matching performance of these order based approaches is high, but, computational complexity and expense are also high. So, a new descriptor, which is simple in computation and less expensive, is required in the area SBD.

Fig.2 Sample frames of a cut transition

Here, in this paper, we have made use of a local descriptor named, Local Contrast and Ordering (LCO)[28], which is very simple and more efficient. Image matching, which locates the correspondences between two frames of the video, based on these extracted feature vectors, is the next step of SBD. In order to make point correspondences between two images, here it is the frames of video, feature matching is performed. Finally the classification will be done according to this correspondence. In the proposed method, Euclidian distance, the fast similarity/dissimilarity matric, is used for comparing the images. Lastly, the transition or no-transition in the shot is decided by this comparison with the help of some threshold. Rest of this paper is ordered as follows. Section 2 gives a short literature about the shot boundary detection process and different feature descriptors. The proposed SBD method is explained in section 3 followed by the results analysis in section 4. Finally, concluded the paper in section 5.

II. LITERATURE REVIEW

Gargi et al.[20] had given a detailed analysis on SBD algorithms. Mainly they focused on color histogram based approaches and proved that it is one among the best methods for abrupt transition detection. They also considered compressed domain techniques like MPEG algorithms in their review, since the compressed domain has become ascendant in video analysis. The temporal video segmentation in compressed domain extracts the features from DCT coefficients and motion strength [21-23]. However, computational efficiency is high whereas, the histogram approaches are better in performance. In the last decades, researchers were more attentive in fuzzy logic for video segmentation. The combination of fuzzy logic and genetic algorithm is used in [24]. The membership function of the fuzzy system is calculated using genetic algorithm, which uses pro-observed actual values for SBD. Final classification is done by fuzzy system. A genetic algorithm search heuristic is used for optimization in [25], in which, no direct threshold used. Edge change ratio metric is used to describe the detection process. Recently D.Asha et al.[26] proposed a novel method towards SBD, using multiple Haar transform features. A procedure based Shot detection algorithm is used for identification of shot transition. Result shows the better performance of this method. A method, particular to dissolve detections suggested by Chong wangh [27]. A dissolve pattern description by Gabor wavelet features and dissolve selection by cut detection in low resolution are showing the novelty of this work. Finally, classification of shot done by SVM. Birinci et al. [19] proposed a generic fast SBD method, which follows the human perceptual rules. Abrupt as well as gradual transitions are considered by extracting local features. Local features can give maximum details about an image. Reduced time complexity is the main highlight, achieved by eliminating the redundant computation.

With the help of geometric and photometric transformation, the relation between two different frames of a shot can be identified. Local image features can be used to achieve this through three step process; initially, by using detectors, extract the interest points from images. Secondly, every interesting point with their neighborhood is represented by distinctive descriptor vector. Finally, the correspondence between image pair is identified by matching these descriptor vectors. Though there are a number of local image features available, it is indeed that selecting a feature descriptor which is fully invariant to illumination changes, rotation, scaling and changes in view point is a great challenge in the area of content based video processing.

Many researchers were approached image matching with binary patterns, which are fast and meet the real time demands. Local Binary Pattern and its multiple extensions, Binary Robust Independent Elementary features (BRIEF), ORB, modified BRIEF etc. are examples of binary pattern based descriptors. An Ultra Short Binary (USB) descriptor is introduced by Shiliang shang et al. [17], which is a 24 bit binary descriptor. Fast image matching and indexing is achieved by this feature. Though the descriptors are very fast in computation, the problem with large distortions still exists in these binary descriptors.

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As we discussed in the introduction, though the local features like SIFT, SURF and SLD are invariant to scaling, rotation in some extend, they are not sufficient for solving the illumination change problems. Order based descriptors like LIOP, IOLD are considering the illumination changes and showing high matching performance. But, the complexity in computation is a drawback for them.
Motivated from all these discussions, we have used a simple and discriminant descriptor, Local Contrast and Ordering (LCO) in our SBD method. It is an order based local descriptor proposed by J. Duo et al. [28], which satisfies the computational cost and matching accuracy.

III. PROPOSED METHOD

After extracting the frames from video, we have to extract the features from those frames. Even feature extraction methods are plenty, each one is lacking in some characteristics. Choosing a befitting feature extraction method is a challenge not only in shot boundary detection, but, in other vision based algorithms. Invariance of a feature descriptor in different distortions is prioritized one, which should be taken care of. Histogram oriented features, like HoG, edge oriented histogram; Transformation based features like DWT, DCT; Texture based features like GLCM; Binary pattern based features like LBP, LTP, BFRIEF, ORB; local features like SIFT,SURF etc. are the customarily used feature descriptors for image matching in Shot Boundary Detection. Some of features like SIFT, are computationally complex. Some are not fully invariant to distortions, some are not fast in computation, and some are not efficient enough to deal with real time demands.
Here, in this paper, we are using a local descriptor named, Local Contrast and Ordering (LCO), for feature extraction, which is very simple, invariant to distortions like illumination changes, rotation, scaling etc. and discriminating one. We are making use of these characteristics of C in our SBD process. Initially, the extracted frames of input video will be converted to gray scale. Then divide each frame into N equal sized non overlapping region of interest. Then for each region, calculate the LCO feature vector separately and finally combine the LCO vectors of each ROI into a single feature vector for ith frame.
The calculation of LCO descriptor for a region of interest in a frame is as follows:
Step 1: *Identify the point of interest q_0.*
Step 2: *Define the Region of Interest (K), with m x m window, surrounding q_0*
Step 3: *Divide the K equally into n x n sub-regions, K_1, K_2, K_3,……., $K_{n\,x\,n}$.*
Step 4: *Calculate the intensity difference of each pixel q_i in K as,*

$$D(q_i) = Intensity(q_i) - Intensity(q_0) \qquad (1)$$

Step 5: *Create two containers to store the qis in K based on the sign of this $D(q_i)$, D_{plus} and D_{minus}.*
Step6: *Sort the contents of D_{plus} and D_{minus}.*
Step 7: *Give the ordering of pixels based on the $D(q_i)$ values.*
Step 8: *To get the exact ordering,*
Do the convolution with an isotopic filter for the pixels with same $D(q_i)$ value.
No change is required for the pixels with different $D(q_i)$ value.
Step 9: *Segment the pixels in D_{plus} and D_{minus} equally into d intervals according to the ordering. d=3 chosen.*
Step 10: *Frame the LCO(P_i) for a sub-region as,*

$$LCO(P_i) = \begin{cases} +1 \text{ if } D(q_i) \text{ is in segment 1 of } D_{plus} \\ +2 \text{ if } D(q_i) \text{ is in segment 2 of } D_{plus} \\ +3 \text{ if } D(q_i) \text{ is in segment 3 of } D_{plus} \\ -1 \text{ if } D(q_i) \text{ is in segment 1 of } D_{minus} \\ -2 \text{ if } D(q_i) \text{ is in segment 2 of } D_{minus} \\ -3 \text{ if } D(q_i) \text{ is in segment 3 of } D_{minus} \end{cases} \qquad (2)$$

Step 11: Store the number of LCO(P_i)s in each category(+1 to -3) in different bins of a histogram. So, each sub region K_i could be represented by a histogram with 6 bins.
Step 12: Combine all sub-region histograms together as in equation (3), and normalize it to a unit vector to increase the robustness.

$$LCO(q_0) = Norm\left\{ \begin{matrix} K_1(-3), K_1(-2), K_1(-1), K_1(+1), K_1(+2), K_1(+3), \ldots\ldots\ldots \\ \ldots\ldots, K_{nxn}(-3), K_{nxn}(-2), K_{nxn}(-1), K_{nxn}(+1), K_{nxn}(+2), K_{nxn}(+3) \end{matrix} \right. \qquad (3)$$

Further, find the collective LCO vector for the entire frame.
After calculating the feature descriptor for every frame in the input video, the next step is image matching. In which, comparing the consecutive frames of video to identify the shot transition. The comparison can be done with similarity/ dissimilarity measures. Commonly used measures are Sum of Absolute Difference, Euclidean distance, histogram difference etc. In our method we used familiar Euclidean distance which is faster in comparison. The Euclidean distance, $\delta(f_t,f_{t-1})$, between two adjacent frames, f_t and f_{t-1}, is calculated with the equation (4).

$$\delta(f_t, f_{t-1}) = \sqrt{\sum_{i=1}^{N} (f_t(i) - f_{t-1}(i))^2} \qquad (4)$$

Where, N is the number of elements in the LCO descriptor vector of each frame, $f_t(i)$ represents the i^{th} element of the LCO vector of tth frame.
Next, an adaptive threshold, Th_{lco}, is calculated from these distance values using the equation (5). Then compare the $\delta(f_t,f_{t-1})$, of adjacent frames with this threshold to locate the cut transition. A cut will be declared, if the $\delta(f_t,f_{t-1})$, of adjacent frames are greater than the Threshold.

$$Th_{lco} = \frac{\max\{\delta(1,0), \delta(2,1), \ldots\ldots\ldots, \delta(m, m-1) * Th_{percentage}}{100} \qquad (5)$$

Where, *m* is the number of frames in the input video, and this threshold is adaptive and is a percentile value of maximum difference.

IV. RESULTS AND ANALYSIS

For analysis of our method we have used TRECVid dataset. Four videos, which include different types of distortions like, illumination changes, rotation, scaling, zooming etc., are specifically chosen from the entire dataset. Videos chosen for experiment are represented as V1 to V5. The description of these videos is given in the table 1.

In order to show the performance of our approach we have compared our method with three other well-known approaches, Scale Invariant Feature Transform, Speeded Up Robust Features and color histogram approach. Comparative result is shown in table 2 and table 3. The result shows that, the LCO feature based method is giving better result than other three feature based methods. Our method correctly detecting the shots even in the cases of large illumination changes, view changes, scale changes and rotation. As we are using only the ordering and sign of intensity values, the time complexity is also very less.
We have evaluated the results with two different measures, recall and precision using the equation 6 and 7 respectively.

Table 1: Description of video sequences

Input video	# of frames in video	Original # of cuts	Length of video (in sec)
V1	29610	96	1478
V2	15210	77	608
V3	28908	162	1156
V4	21960	118	878

Table 2: Ground truths, Cuts detected and False Positives of individual methods

Sequence	Ground truth	SIFT		SURF		Histogram		LCO	
		detected	FP	detected	FP	detected	FP	detected	FP
V1	96	97	8	97	4	95	1	98	3
V2	77	74	5	78	7	76	6	78	4
V3	162	160	8	163	6	166	8	163	4
V4	118	113	3	120	6	118	6	119	3

Table 3: Comparison of Recall and Precision of SIFT, SURF, Histogram and LCO methods.

Sequence	SIFT		SURF		Histogram		LCO	
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
V1	92.7	91.73	96.88	95.87	97.91	98.94	98.96	96.93
V2	89.61	93.24	92.21	91.02	90.9	92.1	96.1	94.87
V3	93.82	95	96.91	96.31	97.531	95.18	98.15	97.54
V4	93.22	97.34	96.61	95	94.91	94.91	98.31	97.47
AVG	92.33	94.32	95.81	94.85	95.31	95.14	97.88	96.55

$$Recall = \frac{\#\ of\ Transitions\ detected\ correctly}{Actual\ \#\ of\ Abrupt\ Transitions} \quad (6)$$

$$Precision = \frac{\#\ of\ Transitions\ detected\ correctly}{Total\ \#\ of\ transitions\ detected} \quad (7)$$

Recall and precision values of our approach is compared with other three methods in table 3. As this LCO descriptor is very simple to establish, the computational efficiency is very high.

Further, we have analyzed the experiment with two parameters, n and d. n is the number of sub regions in the local region and d is the number of ordering intervals. The value of d is taken as 3, same as in [28]. We have done the experiment with the n values 3, 4 and 5. The recall and precision comparison is shown in Fig 4-6. Recall of n=4 and n=5 are similar but when n=3 it is very less. The accuracy of this approach is proportional to the value of n, but, if we select high n value then the LCO descriptor dimension will increase and computation time so as. So we have chosen n=4 for our experiment. Thus the dimension of LCO descriptor is 96, but it is 128 for both SIFT and SURF. So the computational time is less when compared to other methods.

V. CONCLUSION

The proposed method for short boundary detection using texture based descriptor LCO. The LCO descriptor possesses very discriminative nature which is very useful in identifying shot boundaries. Besides, the shot boundary detection became a light weight process as LCO follows minimum computation overhead. The extensive experiments show that this method outperforms the existing methods for SBD. The publically available data sets are used in this method to facilitate repeatability of experiments. Our method improves the accuracy of the SBD. As a future work, need to device methods to reduce computational cost without compromising accuracy of SBD.

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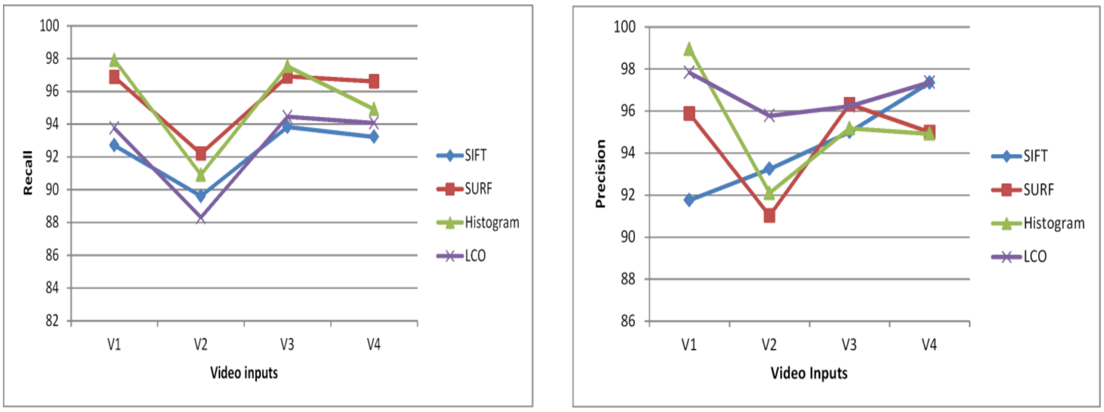

Fig. 4 Comparison of Recall and precision values when n=3, d=3 for LCO

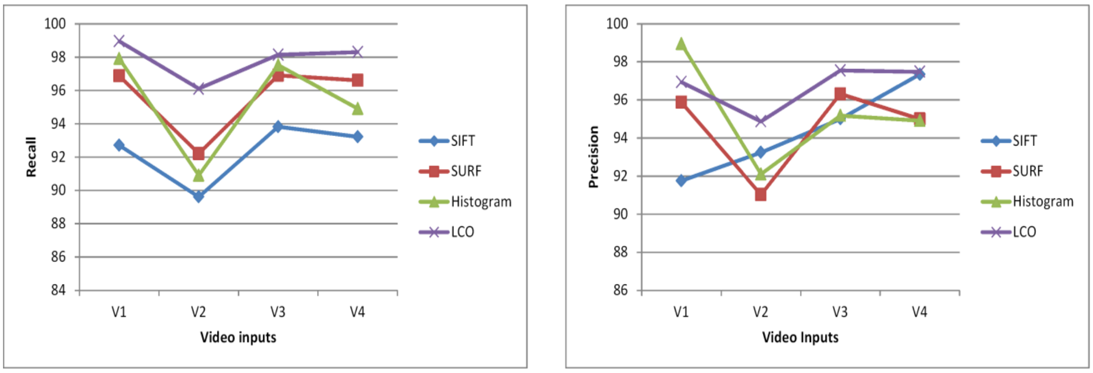

Fig. 5 Comparison of Recall and precision values when n=4, d=3 for LCO

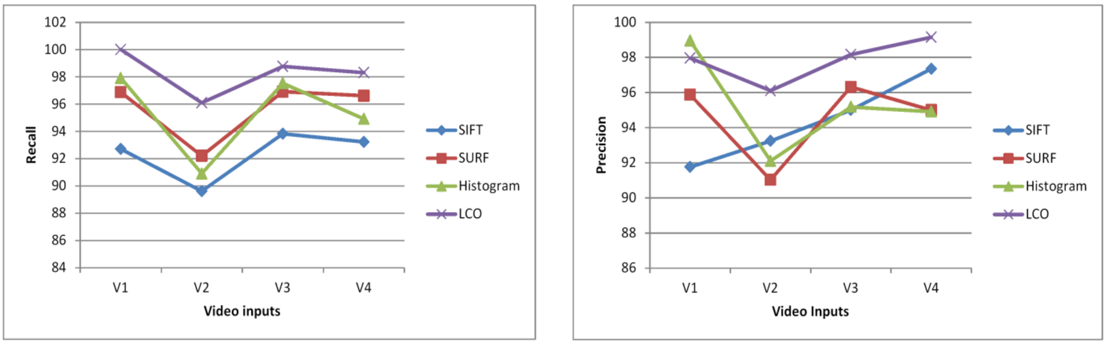

Fig. 6 Comparison of Recall and precision values when n=5, d=3 for LCO

REFERENCES

1. Baber, Junaid, Nitin Afzulpurkar, and Shin'ichi Satoh. "A framework for video segmentation using global and local features." International Journal of Pattern Recognition and Artificial Intelligence 27.05 (2013): 1355007
2. Lowe, David G. "Distinctive image features from scale-invariant key points." International journal of computer vision60.2 (2004): 91-110.
3. El Khattabi, Zaynab, Youness Tabii, and Abdelhamid Benkaddour. "Video Shot Boundary Detection Using the Scale Invariant Feature Transform and RGB Color Channels." International Journal of Electrical & Computer Engineering (2088-8708) 7.5 (2017).
4. Juan, Luo, and Luo Gwon. "A comparison of sift, pca-sift and surf." International Journal of Signal Processing, Image Processing and Pattern Recognition 8.3 (2007): 169-176.
5. Lindeberg, Tony. "Scale invariant feature transform." (2012): 10491.
6. Bay, Herbert, Tinne Tuytelaars, and Luc Van Gool. "Surf: Speeded up robust features." European conference on computer vision. Springer, Berlin, Heidelberg, 2006.
7. Deepak, C. R., et al. "Shot boundary detection using color correlogram and Gauge-SURF descriptors." 2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT). IEEE, 2013
8. Mikolajczyk, Krystian, and Cordelia Schmid. "A performance evaluation of local descriptors." IEEE transactions on pattern analysis and machine intelligence 27.10 (2005): 1615-1630.
9. Sukthankar, Rahul, and Yan Ke PCA-SIFT. "A More Distinctive Representation for Local Image Descriptors." Proceedings of the 2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. USA: 1EEE. 2004.
10. Morel, Jean-Michel, and Guoshen Yu. "ASIFT: A new framework for fully affine invariant image comparison." SIAM journal on imaging sciences 2.2 (2009): 438-469.
11. Youssef, Bendraou, et al. "Shot boundary detection via adaptive low rank and svd-updating." Computer Vision and Image Understanding 161 (2017): 20-28.
12. Yoo, Hun-Woo, Han-Jin Ryoo, and Dong-Sik Jang. "Gradual shot boundary detection using localized edge blocks." Multimedia Tools and Applications 28.3 (2006): 283-300.
13. Thounaojam, Dalton Meitei, et al. "A genetic algorithm and fuzzy logic approach for video shot boundary detection." Computational intelligence and neuroscience 2016 (2016): 14.
14. Zhou, Wen, et al. "SLD: a novel robust descriptor for image matching." IEEE Signal Processing Letters 21.3 (2013): 339-342.
15. Wang, Zhenhua, Bin Fan, and Fuchao Wu. "Local intensity order pattem for feature description." 2011 International Conference on Computer Vision. IEEE, 2011.

16. Dubey, Shiv Ram, Satish Kumar Singh, and Rajat Kumar Singh. "Rotation and illumination invariant interleaved intensity order-based local descriptor." IEEE Transactions on Image Processing 23.12 (2014): 5323-5333.
17. Zhang, Shiliang, et al. "USB: Ultra Short Binary descriptor for fast visual matching and retrieval." IEEE Transactions on Image Processing 23.8 (2014): 3671-3683.
18. Gupta, Raj, Harshal Patil, and Anurag Mittal. "Robust order-based methods for feature description." 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. IEEE, 2010.
19. Birinci, Murat, and Serkan Kiranyaz. "A perceptual scheme for fully automatic video shot boundary detection." signal processing: image communication 29.3 (2014): 410-423.
20. U. Gargi, R. Kasturi, S.H. Strayer, Performance characterization of video-shot-change detection methods, Circuits Syst. Video Technol. 10 (1) (2000) 1–13.
21. Thounaojam, Dalton Meitei, et al. "A genetic algorithm and fuzzy logic approach for video shot boundary detection." Computational intelligence and neuroscience 2016 (2016): 14.
22. Chan, Calvin, and Alexander Wong. "Shot boundary detection using genetic algorithm optimization." 2011 IEEE International Symposium on Multimedia. IEEE, 2011.
23. Meng, Jianhao, Yujen Juan, and Shih-Fu Chang. "Scene change detection in an MPEG-compressed video sequence." Digital Video Compression: Algorithms and Technologies 1995. Vol. 2419. International Society for Optics and Photonics, 1995.
24. K. Shen, E.J. Delp, A fast algorithm for video parsing using MPEG compressed sequences, IEEE International Conference Image Processing, October 1995, pp. 252–255.
25. I.K. Sethi and N. Patel, A statistical approach to scene change detection, in: Proceedings of IS&T/SPIE Conference Storage and Retrieval for Image and Video Databases III, vol. SPIE 2420, 1995, pp. 329–338.
26. Asha, D., and Y. Madhavee Latha. "Content-Based Video Shot Boundary Detection Using Multiple Haar Transform Features." Soft Computing and Signal Processing. Springer, Singapore, 2019. 703-713.
27. Ngo, Chong-Wah. "A robust dissolve detector by support vector machine." Proceedings of the eleventh ACM international conference on Multimedia. ACM, 2003.
28. Duo, Jingyun, Pengfeng Chen, and Long Zhao. "LCO: A robust and efficient local descriptor for image matching." AEU-International Journal of Electronics and Communications 72 (2017): 234-242.

AUTHORS PROFILE

Jasmin T. Jose is currently working as an Assistant Professor in School of Computer Science and Engineering, at Vellore Institute of Technology, Tamil Nadu, India. She received B.E. in Computer Science and Engineering from Anna University, Chennai, India in 2005, MTech. in Computer Science and Engineering from NIT Calicut, Kerala, India in 2013. She is pursuing Ph.D. from VIT University, Vellore, India. Her research interest includes computer vision, video processing and Image processing. She has published many research papers in international conferences and journals. She is a life member of ISTE.

Rajkumar Soundrapandiyan is currently working as an Associate Professor in School of Computer Science and Engineering, Vellore Institute of Techology, Tamil Nadu, India. He received B.E. in Computer Science and Engineering from Anna University, Chennai, India in 2008, M.E. in Computer Science and Engineering from Anna University, Chennai, India in 2010. He has completed Ph.D. at VIT University, Vellore, India in 2017. His research interest includes computer vision, visual perception, object detection, medical image processing, infrared image processing, biometrics, information hiding, and network security. He has published more than 35 research papers in reputed international conferences and journals. He has been involved in one sponsored workshop, sponsored by DHR-ICMR. He is a Reviewer for many reputed journals like Computers in Biology and Medicine, Computers & Electrical Engineering, IET Computer Vision, etc. He is a life member of CSI and senior member of IEEE.