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Key Frame Extraction for Content Based Lecture Video Retrieval and Video Summarisation Framework

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Abstract*: Due to fast expansion in computer and telecommunication industry digital video has become a promising force for its large data storage. Nowadays lecture video and audio data is growing fast and becoming enlarged in internet. Therefore a Video Retrieval and Summarization with effective Key Frame Extraction for content based lecture video search and indexing is presented here by introducing video segmentation and text key frame extraction. Video contents can be extracted through detection of metadata. By applying automated speech recognition and optical character recognition the metadata from the lecture video can be mined. Key frame representation is a powerful mechanism for accessing the video content and key frame extraction is really helpful in retrieving the accurate video content during browsing. Transition Outcome Recognition (TOR) method is proposed to automatically segment the video streams into shots. Optical Character Recognition (OCR) process is used to extract the text key-frames that reduces frame redundancy and captures slide transition in the video shot. Finally, a self-concentration replica is introduced to select key-frames sequences inside shots, thus key static images are selected as video content summarization.

Keywords: Key frame extraction; Transition Outcome Recognition; Video Content Summarization; Self-concentration Replica

1. INTRODUCTION:

The mainstream explore point video data can be important resources in the event that we can make full utilize of it to do numerous important things, for example, utilizing artificial intelligence for security checking or savvy investigation. In any case, a lot of information greatly affect hardware preparing devices, so the video summarization innovation that can remove successful data from amounts of video information therefore it became a mainstream explore point that gives huge interests for scientists. The reason for video synopsis is to introduce a significant dynamic perspective on whole video inside a brief time-frame. The elemental type of video summarization is divided into key edge extraction and video skim.

In general, amount of information in video is huge at different stage of scenes, shots and frames. To find information from video captures the greatest test is to process colossal measure of data present in it. One arrangement is to lessen the excess information present in video which will fundamentally decrease the measure of data that should be prepared. Key casings are the trademark edges of the video which render restricted, however important data about the substance of the video. A strategy dependent is applied on shading histogram and edge location [1] that lessens the computational intricacies. Clustering mechanism of key frame extraction successfully lessens repetitive frames utilizing the mix of region and worldwide data yet is seen as computationally costly [2]. A real-time algorithm for scene change detection and key-frame extraction that generates the frame difference metrics by analyzing statistics of the macro-block features [3] extracted from the MPEG compressed stream. The key-frame extraction method is implemented using difference metrics curve simplification by discrete contour evolution algorithm. But the shot detection technique used can be simplified.

2. RELATED WORKS

Some of the works that related to the key frame extraction in video sequences are described. Automatic summarization and indexing techniques will give users an opportunity to browse and select multimedia document of their choice. Density peak clustering [4] was proposed to cluster less dimensional data and to detect the centre of the clusters. Key frame extraction for various kinds of video can be done by combining different kind of video content. Movement state-versatile video synopsis plot [5] was proposed on premise of spatiotemporal examination. This method utilizes spatiotemporal cuts for investigating object movement directions and movement state changes is taken as a measurement for summing up recordings. By the utilization of movement power the movement dynamic fragment is identified at that point changes are demonstrated as a collinear portion to extricate the key edges. Video age outline emergency is detailed as a Maximum Posteriori Probability (MPP) assessment [6] trouble where the positions and showing up frames of video objects are sequentially improved progressively without the need to know their total directions. Besides, a summarization table is utilized with MPP estimation to choose the transient areas of the approaching closer view protests in the abstract video without requiring an enhancement methodology.

Divide-and-conquer based framework [7] was proposed an effective outline of large video information. The first video information is portioned into shots, where a consideration model is figured from each shot in equal. Viewer's consideration depends on various tangible discernments like aural and visual. The aural consideration model depends on the Teager vitality, moment abundancy, and moment recurrence, though the visual consideration model utilizes multi-scale differentiation and movement power. A totalled consideration bend is created utilizing an intra-and between methodology combination system and henceforth the full of feeling content in every video shot is removed. An effective visual consideration model based key edge extraction technique [8] was proposed here the computational expense is decreased by utilizing the worldly inclination based unique visual saliency recognition rather than the customary optical stream strategies. In addition, for static visual saliency, a compelling strategy utilizing discrete cosine change has been utilized. The static and dynamic visual consideration measures are combined by utilizing a non-direct weighted combination strategy. A way to deal with separate the most alluring key edges was proposed by utilizing a saliency-based visual consideration model [9] that overcomes any issues between semantic translation of the video and low-level highlights. To start with, dynamic and static conspicuity maps are developed dependent on movement, shading and surface highlights. At that point, by presenting concealment factor and movement need plots, the conspicuity maps are intertwined into a saliency map that incorporates just evident consideration areas to deliver consideration bend.

Keypoint-based system [10] was proposed to address the keyframe determination issue with the goal that nearby highlights can be utilized in choosing keyframes. Commonly, chosen

keyframes should both be illustrative of video content and containing least excess. In this way, in determination process standards; inclusion and excess are utilized on premise of key-point coordinating. Efficient search and navigation of video content was particularly designed for Slide Based Lecture Videos (SBLV) [11] that represents a significant portion of online lecture videos. The interface comprehensively derives versatile semantic clues for video content indexing and visual aid generation according to visual elements, text, and mathematical expressions included on lecture slides, speeches recorded, as well as mouse and cursor pointing actions captured during a lecture. A strategy that together endeavours low-level and significant level features [12, 22] was proposed for the consequently separated from the visual and the sound-related channel. This procedure is based upon the notable strategy for the Scene Transition Graph (STG), first by presenting another STG estimation that features diminished computational expense, and afterward by broadening the unimodal STG-based worldly division procedure to a technique for multimodal scene division.
A structure for an effective Video SUMMarization (VSUMM) [13] just as video movement synopsis was proposed. At first, Capsules Net is prepared as a spatiotemporal data extractor, and a between outlines movement bend is produced dependent on those spatiotemporal highlights. Consequently, a progress impacts discovery strategy is proposed to naturally portion the video streams into shots. At long last, a self-consideration model is acquainted with select key-frames arrangements inside the shots; in this manner, key static pictures are chosen as video content rundown, and optical streams can be determined as video movement synopsis. A methodology for key edge extraction was proposed [14, 18,22] dependent on the square based Histogram distinction and edge coordinating rate. Initially, the Histogram distinction of each casing is determined, and afterward the edges of the competitor key edges are extricated by Prewitt administrator. Finally, the edges of nearby edges are coordinated. If the edge coordinating rate is better than expected edge coordinating rate, the present casing is esteemed to the repetitive key edge and ought to be discarded.
Static video summarization is recognized as an effective way for users to quickly browse and comprehend large numbers of videos [15]. Along these lines static video frame is planned as a grouping or clustering issue. Inspired by the thought from high density tops inquiry grouping calculation, a powerful clustering calculation was proposed by incorporating significant properties of video to accumulate comparable frames into clusters. At last, all clusters' centre will be gathered as static video synopsis. This clustering based video synopsis can identify outlines which are exceptionally significant and produce agent groups naturally. Video skimming [16] commonly considered as a noteworthy strategy for video rundown, lets end clients progressively peruse full-length recordings in a constrained time. Video skimming removes significant portions and reassembles them into a short video cut. Contrasted with its static partner key-frames, video skimming has focal points in expressiveness and grandness, since it stays as video, yet is increasingly entangled and requires a superior understanding of video content. Two phase User guided Video Segmentation (TUVS) structure [17-22] was recommended that incorporates measurement decrease and fleeting grouping. During the measurement decrease stage, a coarse granularity feature extraction is directed by a profound Convolutional Neural Network (CNN) pre-prepared on ImageNet. In the temporal grouping stage, the data of the client's expectation is used to fragment recordings on time space with a proposed administrator, which ascertains the closeness separation between dimensions reduced frames. To give more understanding into the recordings, a hierarchical strategy that permits clients to section recordings at various granularities.

3. PROPOSED WORK

Content Based video retrieval framework for lecture video includes key frame extraction and representation that provides a better and effective video summarization without any frame redundancies. Therefore Video Retrieval and Summarization with effective Key Frame Extraction (VRS-KFE) is proposed. Initially the video is segmented into shots and the inter-frames motion curve is obtained. This process of clustering extracts the spatiotemporal features. From the segmented video the text extraction process is carried out by applying OCR in the keyframes. The keyframes are extracted from the title region and content region of the lecture video slides. Then the video content summarization process is developed after the retrieval of video successfully. The flow diagram of VRS-KFE is described in figure 1.

(i) Transition Outcome Recognition

The edited or updated video may gone through many changes like crop cut, fading effects, dissolving effects etc. Fading effects includes fade in and fade out that are the special cases comes under dissolving effects. Dissolving effects describes about mixing of content shots i.e. content of first shot images mixing with the content of second shot images due to global motion. The zoomed description of the panorama can be described as crop cut effect. It occurs due to rapid change also it consumes more time for transformation from one shot into another. This leads to violent vibration in the curve that is caused by traditional features. On basis of the changes occurred in the curve the transition outcome is recognized. TOR is carried out based on link error and sliding windows. The link error is identified when exist a continuous modifying regularity in the curves. Curve fit requires two stop-points in the local series, so that the local curve fairness can be achieved by taking the link error judgement.

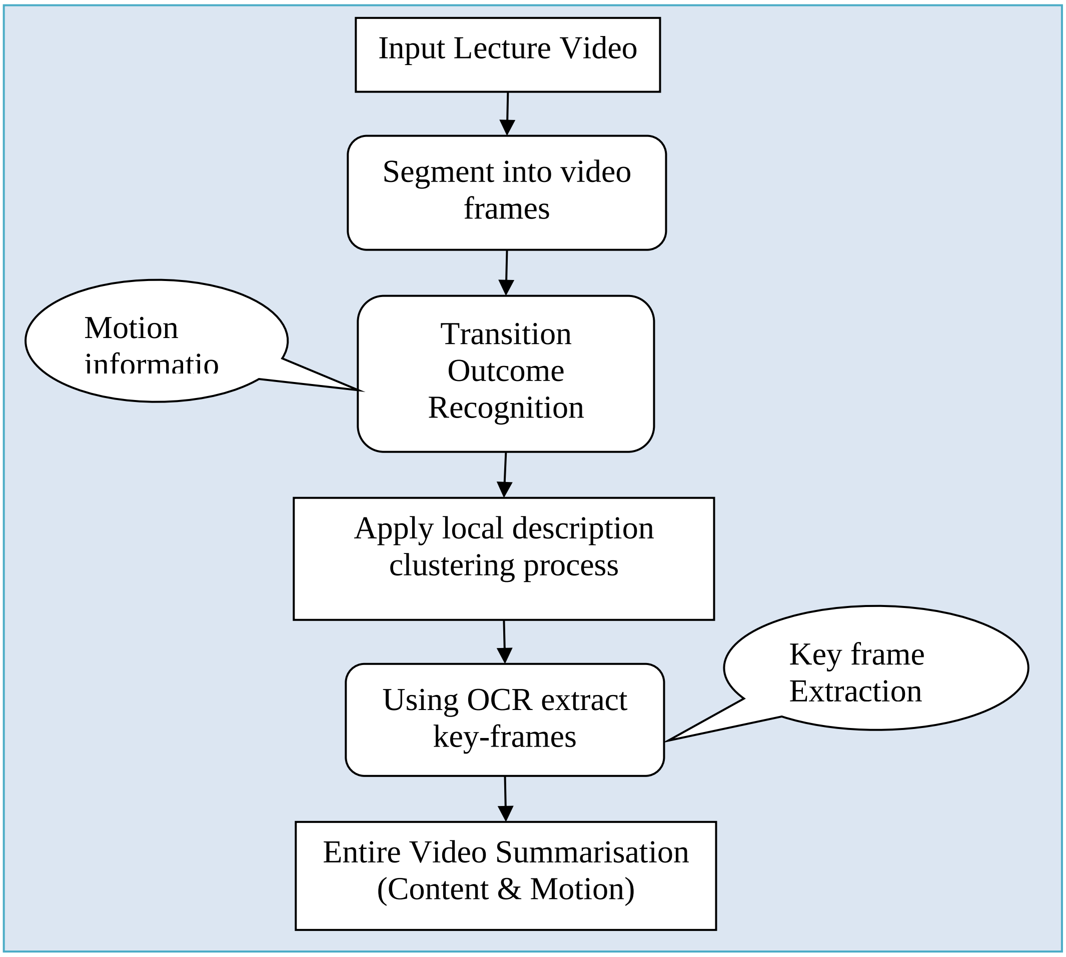

Figure 1: Flow diagram of VRS-KFE

Algorithm of TOR

Input: Video shots
Output: Types of Transition Outcome

1: Initialise feature extractor
2: Split video into video shots
3: Obtain inter-frames motion curve feature vector
4: Identify link error and compute sliding windows
5: Assign sliding window point and calculate $G^1(SW_{s,p'}, SW_{s+1,p''}) \& G^1(SW_{s-1,p'}, SW_{s,p''})$
6: Compute link errors among SW's ← transition outcome phase
7: if $\left|G^1(SW_{s,p'}, SW_{s+1,p''})\right| > 3\left|G^1(SW_{s-1,p'}, SW_{s,p''})\right|$ *→ video transforms from one shot t other shot*
8: end if
9: if $\left|G^1(SW_{s,p'}, SW_{s+1,p''})\right| > 1/3\left|G^1(SW_{s-1,p'}, SW_{s,p''})\right|$ *→ New shot begins & previous shot ends*
10: end if
11: Apply Gaussian distribution function
12: Detects types of transition outcome
13: end

The control points are assumed for the curves. Let p0, p1, p2,…, pn are the control points of the previous curve and m0,m1,m2,…, mn are the control points for the next curve. For G^0-link pn=mo, therefore for G^1-link normal lines of two curves are same and it is computed using equation 1.

$$G^1(\mathrm{m_i}, \mathrm{p_j}) = (m_1 - m_0) - \lambda(\mathrm{p_n} - \mathrm{p_{n-1}}) \tag{1}$$

At this point the tangent angle is 0 degree, where i=1…n, and j=1…n. Here, the transition effect is recognized mostly for 18 frames. Sliding window is constructed with the length of 12 and pace value is set to 6. Each time 6 frames will be calculated and therefore the transition outcome is calculated for three sliding windows and curve fit is carried out for each window. Local curve oscillation intensity is measured by using the transition number of frames and G^1 link error occurred among the sliding windows for each shot boundary consideration. The Sliding Window Point ($SW_{s,p}$) of s^{th} located in curve is $(1 \le s \le \left(N - 12 - 1\!/\!6\right) + 1)$, where N represents the video frame length and point p=1,2…12 present in sliding window. When the pace value is 6; then sliding window point is represented using equation 2.

$$SW_{s-1,p} = SW_{s,p'}(\mathrm{p'}=7,\ldots,11;\mathrm{p''}=1,\ldots,6) \tag{2}$$

The three sliding windows is considered here such as $SW_{s-1,p}$, $SW_{s,p}$, and $SW_{s+1,p}$. The G^1 link errors between these three sliding windows $G^1(SW_{s-1,p'}, SW_{s,p''})$ and $G^1(SW_{s,p'}, SW_{s+1,p''})$ are taken as criterion. The video transform into the transition outcome phase if it satisfies the condition given in equation 3.

$$\left|G^1(SW_{s,p'}, SW_{s+1,p''})\right| > 3\left|G^1(SW_{s-1,p'}, SW_{s,p''})\right| \tag{3}$$

In this condition the previous shot ends and the link curve changes its transition state dramatically. The new shot begins when the sliding window transition reaches the condition given in equation 4.

$$\left|G^1(SW_{s,p'}, SW_{s+1,p''})\right| > 1/3\left|G^1(SW_{s-1,p'}, SW_{s,p''})\right| \tag{4}$$

As per these boundary conditions, shot boundary can be identified. The types of transitions are judged and evaluated by combining the frame length of transitions and G1 link error and it is given in equation 5.

$$TR = e^{-(K^2/2xc^2)} \times \left|G^1(SW_{s,p'}, SW_{s+1,p''})\right| - \left|G^1(SW_{s-1,p'}, SW_{s,p''})\right| \tag{5}$$

Here c=12, and Gaussian distribution function is used in the first part to detect the crop cut effect that assigns higher values for smaller duration parts. Therefore the TOR automatically divides the video streams into shots. The relationship between the transition outcome value and the TR is given in table 1.

Table 1: TOR Conditions

Transitions	Conditions
Crop-cut	6<TR<12
Dissolve	3<TR<6, s>12
Fading	3<TR<6, s<12

(ii) Applying OCR for text key-frame extraction

The slide transitions are captured in the video segmentation process. The database consists of the entire slide content information. The similar contents from each slide are measured using invariant feature transform. OCR is applied to extract the metadata from the slide streams in order to retrieve the video with more accuracy. The text key-frames are extracted from the title and content area of the slides using OCR. The text lines in the slides are classified in to key point, content text and foot line. The classification of text is carried out on basis of height and width of the text line object. All the Connected Components (CC) of frames are detected using canny edge detection process. By applying threshold value (set to be '1') for title and content area of the slides the extraction process is carried out. Any modifications in title area lead to transition of slides. If no difference in title area, then first and last object is detected and performs frame connected component variance among the region. If difference value among the frames goes above the threshold value then the transition of slide is confined. The extracted frames on basis of threshold value the title and content area analysis is carried out and the key-frames are extracted. The key frames from the OCR text extraction and testing extraction are compared using the metadata information stored in database. If both the key-frames get matched, then the video can be retrieved successfully. This process mainly reduces the redundancies for video indexing.

Algorithm for text key-frame extraction

1: Input video↔ Lecture video
2: Segmentation of videos into shots
3: Frames extracted using canny edge detection process
4: Apply OCR for text extraction in training set
5: Slide transition is captured if Th varies in title & content area.
6: Key-Frame is selected if text matches with test data.
7: Video retrieved successfully.

(iii) Video Content Summarisation

To select the key-frames inside the shot Self Concentration method is applied that consists of sequence encoding process. To find the internal consequences inside the sequences this self concentration model is used. Data at all scenes in the sequences can be accessed in straight, and source sequences data in the decoding process can be directly conceded to all steps. Its resolution is given in equation 6.

$$y_T = f(a_T, X, Y) \tag{6}$$

Where X and Y are different sequences and A= (a_1, a_2,…a_T) is the object vector of T, y represents the mapping function of transformation. Self concentration outcome is achieved if X=Y=A, by using this relationship the internal consequences can be identified for the inside sequences.

The intermediate point is set between the highest value and the lowest value, so that the concentration value is set as the reference for key frame selection. For stable optical flow calculation the key frame series is used in the corresponding video shot. In the concentration curve, the highest point of value is chosen as sub-summary of video shot. These sub-summaries shots are the key frame representation that is used to concatenate the content of the entire video summarisation.

To get effective key frame sequences from OCR process, Key Pair Distances (KPD) is measured which is the difference between original sequences and copied sequences. It is given in equation 7.

$$KPD(X, Y) = \sum_{i=1}^{n} d(x_i, y_i) \tag{7}$$

To reduce the redundancies the effectiveness of key-frames sequence is measured and it is given in equation 8.

$$Count(X, Y) = KPD(X, Y) \times K_a \tag{8}$$

Here K_a → represents the average number of key frames. The lower the count is, the closer the key-frame sequence can place well to the original one.

For video content summarisation the performance is quantitatively measured using F-count value that includes both accuracy and recall of the key-frames. It is given in equation 9.

$$F\_count = \frac{2 \times accuracy \times recall}{accuracy + recall} \tag{9}$$

Here ‘accuracy’ represents the ratio of number of identical frames to the number of frames present in the summary and ‘recall’ represents the ratio of number of identical frames to the frames present in the user summary.

4. RESULTS AND DISCUSSIONS

Two different types of lecture videos are taken for analysis. Video type 1 consists of lecture video with slide view and presenter view at different time intervals. Video type 2 consists of both slide view and presenter view in the same panel. Both videos are taken from machine learning domain. Screen shots of the video are taken here for representation. The experimentation is performed in an Intel Core i5-4210 CPU with 8.00GB RAM, with Windows operating system. VRS-KFE, VSUMM and TUVS methods are developed using MATLABR2015b.

Two types of Machine learning lecture videos are taken for experimentation. Figure 2 shows the video snapshot of slide view and presenter view while figure 3 gives the video snapshots of slide views along with presenter in the bottom of the leftmost corner. Similarity measure is calculated among the words between the two videos. The distance between various data points is termed as similarity measure.

Word-Caption coalition mechanism is used to find optimal path between the word and caption in these two types of lecture video by extracting the key-frames. Sequence W is the keyword in the sentence and sequence C denotes the caption in the sentence and the similarity value is measured on basis of word and caption in the presented input video. The slide detection accuracy is done using the caption in the sentence and the caption from the source is always preferred for higher accuracy for the lecture videos. This makes the video much more resourceful.

In order to identify the key frames at various time intervals the pixel difference is applied to the video frames.

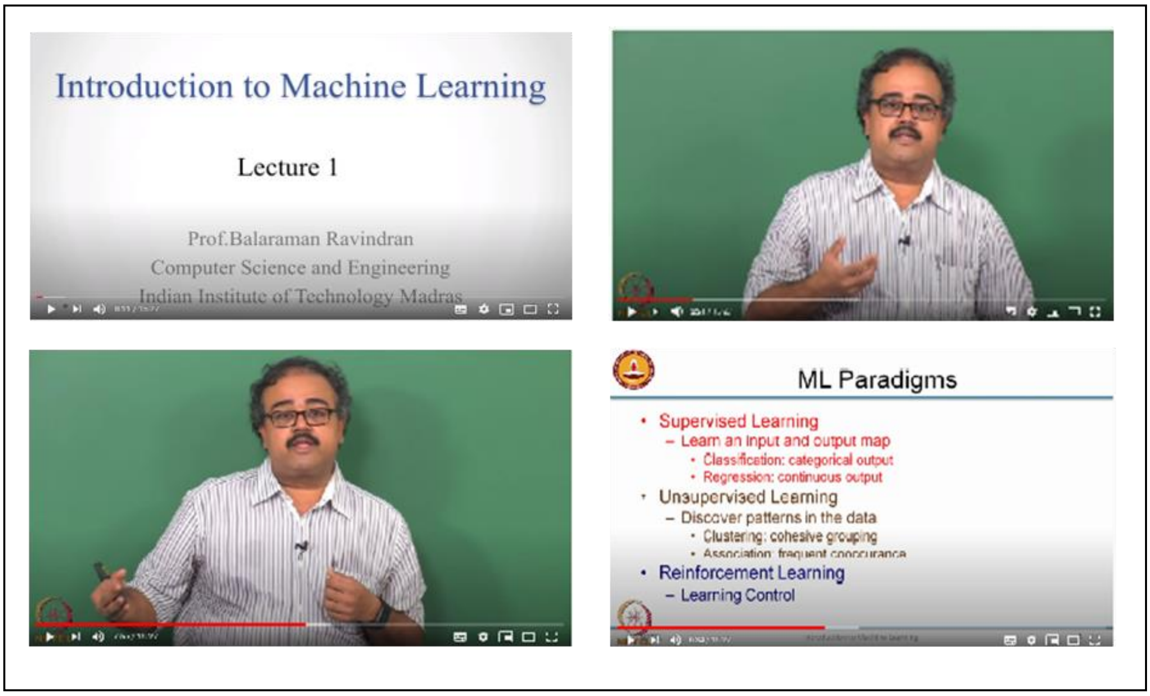

Figure 2: Video Type 1 used for experimentation

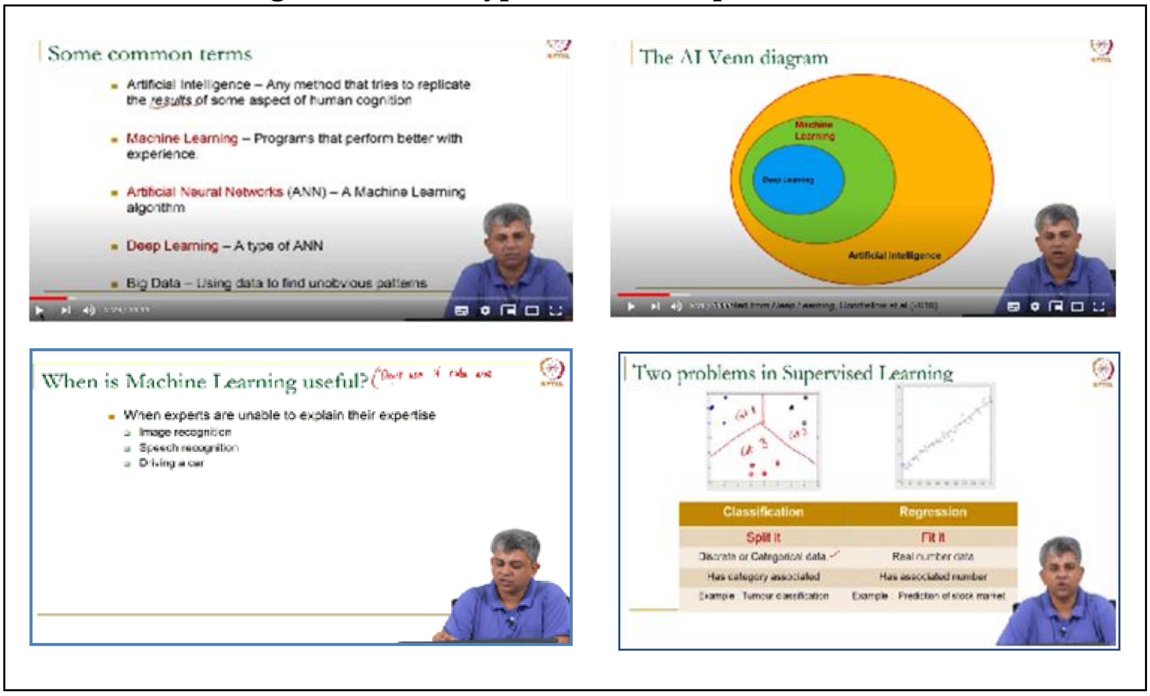

Figure 3: Video Type 2 used for experimentation

The performance of processing time between the two videos and the video slide change detection accuracy are identified. This can be done by taking accuracy and recall evaluation for the particular videos. The video type 1 is divided into 4 snapshots such as V1S1, V1S2, V1S3 and V1S4 simultaneously the video type 2 is divided into four snapshots such as V2S1, V2S2, V2S3 and V2S4. The accuracy value can be calculated using equation 10 and recall value can be calculated using equation 11.

$$Accuracy = \frac{Accurate\ no.of\ recognised\ shot\ change}{No.of\ random\ shot\ changes} \tag{10}$$

$$Recall = \frac{No.of\ recognised\ Shot\ change}{Actual\ no.of\ shots} \tag{11}$$

From the experimental results it is observed that the average accuracy value of proposed method VRS-KFE is 98.6% but the average processing time for VSUMM and TUVS are 89.3% and 95.2%. It shows the improvement of 3.4% in terms of accuracy over TUVS. Figure 4 shows the accuracy values of proposed and conventional methods.

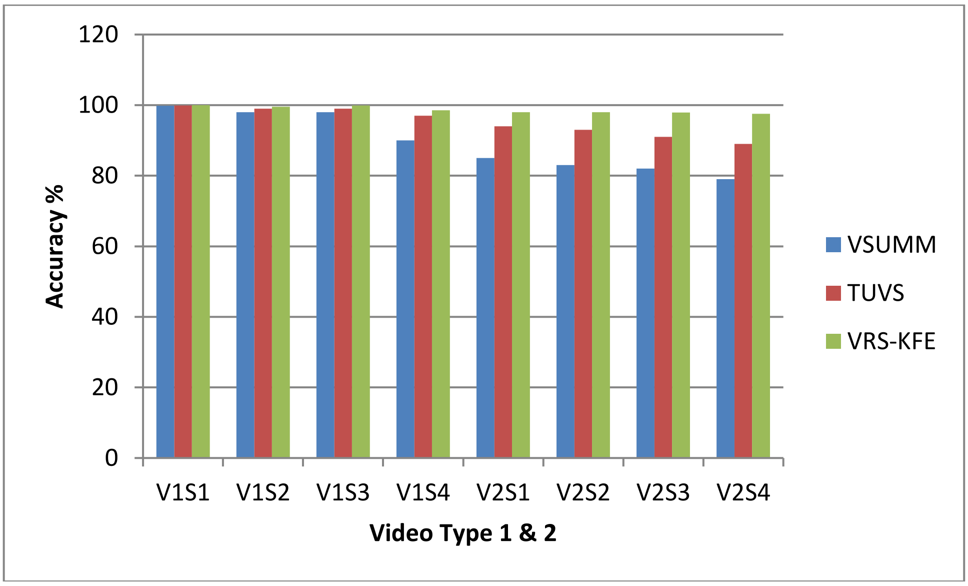

Figure 4: Accuracy

The processing time is reduced 73.75% on average in VRS-KFE method compared to conventional schemes VSUMM and TUVS. Figure 5 represents the processing time of proposed and conventional schemes. The obtained recall values of proposed VRS-KFE and existing VSUMM and TUVS is shown in figure 6. The recall value is reduced for VRS-KFE since the frame interval time is increased. The average recall of proposed method is 67.75 and conventional schemes VSUMM and TUVS are 85.75 and 72.12. The recall rate is greatly reduced for the proposed method VRS-KFE.

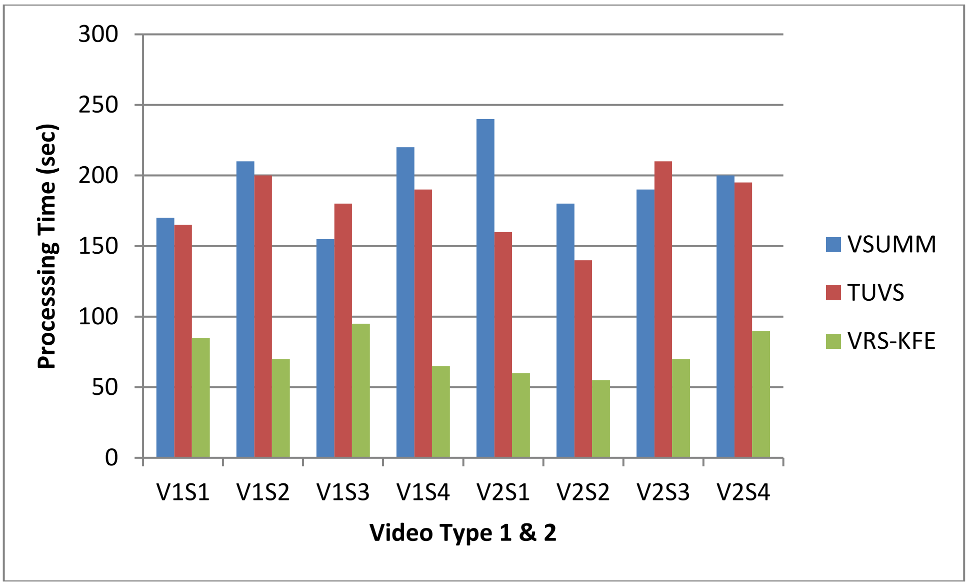

Figure 5: Processing Time

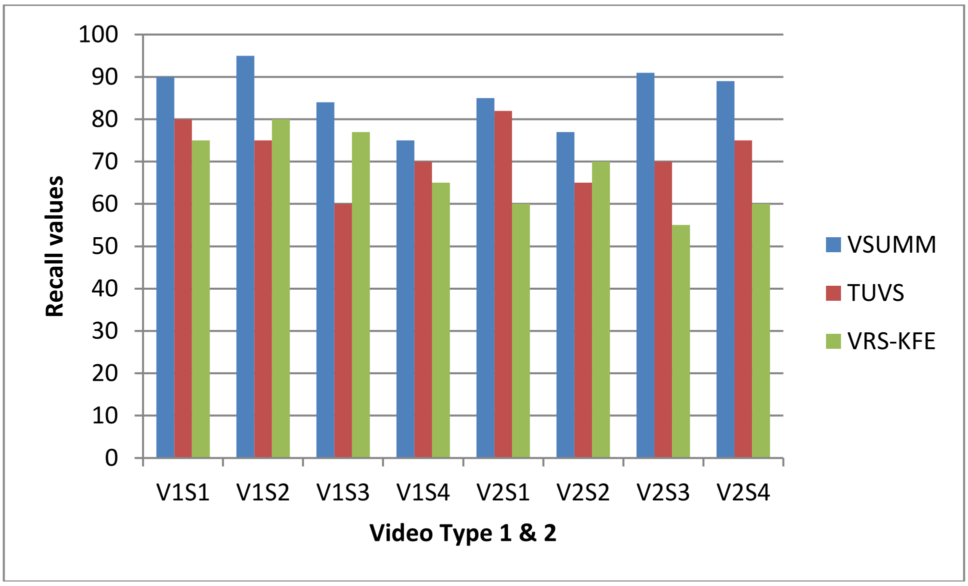

Figure 6: Recall

5. CONCLUSION

Video Retrieval and Summarization with effective Key Frame Extraction for content based lecture video search and indexing is proposed here. Initially the video is segmented into shots and the inter-frames motion curve is obtained using clustering process. Key frame representation mechanism is utilized for accessing the video content and key frame extraction is utilized in retrieving the accurate video content. TOR method is proposed here to automatically segment the video streams into shots. Key frame extraction is done using OCR process that reduces frame redundancy and captures the perfect shot. Self-concentration replica is introduced and the key-frames sequences inside shots are selected. By using the matched key-frames from the OCR text extraction and test data the video is retrieved successfully. Finally video content summarization process is carried out. Experimental results are analysed in terms of processing time, accuracy and recall and proves the proposed VRS-KFE method is better for the analysed criteria.

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