On Retrieval of Nearly Identical Video Clips with Query Frame

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***Abstract*— Video clips retrieval from a video database is a challenging problem for researchers because of voluminous data. Video Clips retrieval with query frame finds the video clips that have similar frames to query frame. Applying matching to all frames of any video clips is time consuming and computationally complex for database containing of several large size video clips. In the present article, we present a three level near identical video clips retrieval algorithm. In the first step, we identify keyframes of video clips in database through establishment of shot transition boundaries and then on keyframes of video clips we apply Integration of Curvelet transform and Simple Linear Iterative Clustering algorithm (SLIC) to get segmented query frames. In the second step, query frame will undergo Integration of Curvelet transform and Simple Linear Iterative Clustering algorithm to get segmented query frames. Now in the third step, the segmentation results of query frame are searched to obtain matched result in database. The method is experimented on 25 different video clips belonging to the categories- animations, serials, personal interviews, news and movies. Performance of the method is assessed with the parameters Precision, Recall, F-measure, Accuracy, Detection Percentage, Jaccard Criteria, and Missing Factor. The furnished performance results have shown sound performance of the proposed method over the other state-of-art methods.**

Keywords*— *Video clips retrieval, Curvelet, Simple linear iterative clustering, detection percentage, accuracy and missing factor

I. Introduction

The latest technology made high quality video capturing devices and web services vastly available to the public at low price which lead to capture, store and share videos in a large amount. Applications like video on demand, TV casts, e-learning and surveillance videos need to be accessed regularly from the database and pointed the need of proper video storage and retrieval system. Video retrieval methods are classified into two categories based on content [1] and concept [2]. An example of a concept based video search engine is YouTube, in which a text query is used to search and retrieve video clips on demand. The main drawback of concept based video retrieval is keywords should be more specific otherwise performance of the system will deteriorate. Thus a content based video retrieval system is proven to be effective for retrieval of near identical videos. A content based video retrieval system may use single image or sequence of frames as query. Generic approach towards content based video retrieval system is segmentation of videos into shots and extraction of keyframes, then features of these keyframes are used to represent video clips. Although, content based video retrieval system is more effective, performance of the system depends on proper shot segmentation and keyframe extraction.

In the present article, we propose a novel content based video retrieval system which consist of three phases: offline, online and matching & a retrieval. In offline phase of the proposed algorithm, shot segmentation and keyframe extraction is done using the method presented in Mounika *et al.* [3] in which pearson correlation coefficient and higher order color moments are used. Then keyframes are segmented using Integration of curvelet and unsupervised simple Linear iterative clustering (*SLIC*) and these segmentation results are used to represent the video clips in database. In online phase query image is given as input to the proposed system and the query image is segmented using *ICTSLIC.* In the third phase, the query frame segmentation results are compared with the segmentation results of videos in database, to acquire near identical videos matched to query image. The proposed method is tested on categories of animations, serials, personal interviews, news, movies and songs videos. The comparative performance analysis of the proposed method with the other state-of- art methods have shown the better performance of the proposed method over other methods.

Rest of the paper is organized as follows: In Section 2. we outlines literature review; Section 3 introduces about the proposed method and section.4 discusses experimental results and Conclusion are given in Section. 5.

II. Literature Review

Vast availability of high speed internet facilities, Cpature & storage devices left huge amount of data on each persons device. Surveillance videos [5, 6] needs to be accessed frequently and needs an efficient retrieval sytem. The work done in the area of video retrieval is few-and-far between. An approach for lecture video indexing and retrieval has been introduced by Yang *et al*. [7] using Optical Character Recognition (OCR) technology and Automatic Speech Recognition (ASR). A local binary pattern variance (LBPV) based video clip retrieval was developed by Shekar *et al.* [8]. Dias *et al.* [9] developed EnContRA, a multimedia information retrieval, which support rich multimodal queries. *Slim²-tree, a*n efficient single indexing structure algorithm of video retrieval was developed by Sperandio *et al*. [10]. Sandeep *et al.* [11] proposed a video retrieval system based on perceptual hashing and Tucker decomposition, for retrieval of near identical videos. Seo *et al*. [12] had introduced a video retrieval system based on ordinal features in which videos containing frames relevant to query video clip are retrieved.

III. Proposed Method

The proposed content-based video retrieval search uses query by image framework to retrieve near identical videos.

The proposed algorithm consists of three stages: offline processing, online processing and matching & a retrieval. Offline processing deals with temporal segmentation of video into shots and then extracts keyframes of these shots. Then, the extracted keyframes are spatially segmented using the algorithm ICTSLIC and these results are used to represent video. In online processing the query image is segmented using ICTSLIC and these results are matched with the segmented keyframes stored in database. Block diagram of proposed method is shown in Fig.1. A brief description of important modules are given below-

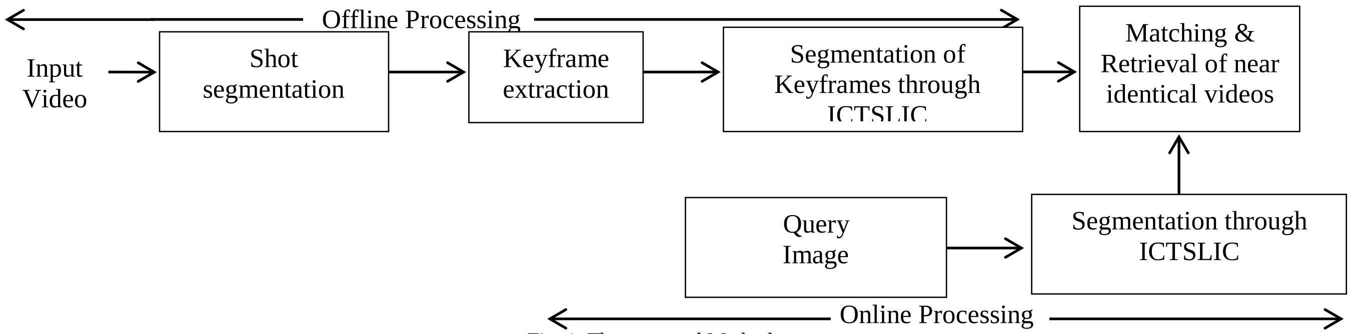

Fig. 1. The proposed Method

Shot segmentation and keyframe extraction-

In [3] shot transition boundaries are established using pearson correlation coefficient and higher order color moments. For every shot the frame with highest standard deviation have been chosen as keyframe.

Segmentation of Keyframes through ICTSLIC-

An unsupervised k-means clustering based Simple Linear Iterative Clustering (SLIC) algorithm have been developed by Achanta *et al.* [13]. SLIC algorithm generates superpixels based on their color similarity in CIElab color space and spatial proximity in the image plane with help of distance measure. The distance measure can control expected cluster size and spatial extent of superpixels. SLIC is a simple and efficient algorithm and is developed for both the color and gray scale images. Integration of Curvelet transform and Simple Linear Iterative Clustering algorithm (ICTSLIC) used to generate superpixels. ICTSLIC is a variant of SLIC where the clustering based on spatial CIElab color components is replaced by the curvelet coefficients of CIElab color components and the same clustering procedure is repeated at different decomposition levels of curvelet transform. The final segmentation result is obtained by refining the results obtained at all decomposition levels and also the results obtained in spatial domain.

Matching-

Euclidean distance between segmentation results of each video stored in database and the segmentation results of the query image are calculated and stored in an array. Now the top ten videos with minimum distance are retrieved.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The proposed method has been tested on dataset containing 30 videos taken from different categories- animations, serials, personal interviews, news, movies and songs. From each category 5 videos were taken and each video of each category is of length 20,000 frames. The proposed methods performance is evaluated both qualitatively and quantitatively.

A. *Qualitative Evaluation*

In offline phase, each and every frame of a single video were extracted and then applied the method described in [3] to extract keyframes. Keyframes obtained are resized to 256×256, and then ICTSLIC segmentation is applied to all keyframes and the segmentation results are stored with proper manual index. Likewise, the above said procedure is carried out on all videos of dataset.

Query Image Generation- From a single video according to the length of that particular video a proper interval have been designed so that 100 query images selected for that video. Likewise, query images for all the videos of database were generated. All the query images are resized to 256×256.

In online phase, for each query image ICTSLIC is applied and this result is searched for a matching result in database by calculating euclidean distance between the segmentation result of query image and the segmentation results stored in database. Now these Euclidean distances are sorted out in ascending order, now the top ten videos for which the Euclidean distance is less are taken as the retrieval result. For few given queries top three retrievals of the proposed approach are shown in Fig. 2. From the visuals shown in Fig. 2 we observe that for a given query at the first place video of exact match to the query image have been retrieved. Not only for single query for all the queries of all category videos at first the video of exact match to the query have been retrieved and in the next places the relevant match to the query were retrieved.

B. *Quantitative Evaluation*

To evaluate effectiveness of the proposed approach, the proposed method is tested with the methods of Shekar *et al.* [8] and Sandeep *et al.* [11]. The quantitative performance analysis of the proposed method and other methods is carried out using the parameters-precision, recall, F-measure, Jaccard index, missing factor, specificity and accuracy and they are given as-

Precision (P) denotes the fraction of retrieved videos that are relevant to a query and mathematically given as-

$$P = \frac{TP}{TP + FP} \tag{1}$$

Recall (R) denotes fraction of relevant videos that are retrieved and mathematically given as-

$$R = \frac{TP}{TP + FN} \tag{2}$$

F-measure (F) denotes the weighted harmonic mean of precision and recall and mathematically given as-

$$F = \frac{2*(P)*(R)}{P + R} \tag{3}$$

Jaccard index (J) gives best matching between two sets and is mathematically given as-

$$J = \frac{TP}{TP + FP + FN} \tag{4}$$

Missing Factor (mf) gives the fraction of relevant items not retrieved and mathematically given as-

$$mf = \frac{FN}{TP} \tag{5}$$

Specificity is also known as true negative rate and mathematically given as-

$$Specificity = \frac{TN}{TN + FP} \tag{6}$$

Accuracy denotes the degree of congruence between the retrieved result and ground truth, mathematically given as-

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{7}$$

Where,

True Positive (TP) – Number of relevant videos that the algorithm correctly retrieved

True Negative (TN) – Number of irrelevant videos that the algorithm not retrieved

False Positive (FP) – Number of irrelevant videos that the algorithm wrongly retrieved

False Negative (FN) – Number of relevant videos that the algorithm not retrieved

The range of Precision, Recall, F-measure, Jaccard index, specificity and accuracy is [0 1] and for an accurate system the above values should be higher. The value of missing factor should be less. The values of Precision, Recall, F-measure, Jaccard index, Missing factor, specificity and accuracy for the proposed method and the other methods [8, 11] is calculated for all the 100 query images of a single video is calculated and then averaged to get final performance. The averaged values over 100 queries of Precision, Recall, F-measure, Jaccard index, Missing factor, specificity and accuracy for the proposed method and the other methods [8, 11] are furnished in Table. 1. The proposed method has shown best performance in terms of Accuracy, Precision, Recall, F-measure, Jaccard index, Missing factor and specificity for all the videos tested under categories of animations, serials, movies and songs. For all videos belonging to personal interviews category the proposed method given best performance than the other methods [8, 11] only in terms of Accuracy, Precision, Missing factor and specificity. For few videos of personal interview category the proposed method failed to produce better values of Recall, F-measure and Jaccard index than the other methods [8, 11]. For the videos of news category the proposed method has shown better values of Accuracy, Precision, Recall, F-measure, Jaccard index and missing factor than the other methods [8, 11]. For videos of news category the proposed method failed in delivering better values of specificity than the other methods [8, 11]. With the above discussion, we can say that the proposed method performs better than other methods [8, 11].

Query Top 3 Retrieval Results

a)

b)

c)

d)

e)

f)

Fig. 2. An example query of each category and its top 3 retrieval results

TABLE I. PERFORMANCE ANALYSIS OF THE PROPOSED AND THE OTHER METHODS [8, 11] FOR DIFFERENT CATEGORIES OF EACH VIDEO

Video	Method	Accuracy	P	R	F	J	mf	Specificity
Category – Animations								
1	Shekar *et al*.[8]	0.1667	0.1	0.3173	0.1521	0.1000	2.7212	0.0909
	Sandeep *et al*. [11]	0.1667	0.1	**1**	0.1818	0.1000	90	0.0909
	Proposed	**0.2683**	**0.3173**	**1**	**0.4818**	**0.1971**	**0**	**0.2335**
2	Shekar *et al*.[8]	0.1667	0.1	0.1530	0.1209	**0.1000**	6.6250	0.0909
	Sandeep *et al*. [11]	0.01	0.01	0.01	0.01	0	99	0
	Proposed	**0.1805**	**0.1530**	**1**	**0.2654**	0.0843	**0**	**0.1300**
3	Shekar *et al*.[8]	0.1667	0.1	0.1451	0.1184	**0.1000**	7.8480	0.0909
	Sandeep *et al*. [11]	0.1667	0.1	**1**	0.1818	**0.1**	8.8	0.0909
	Proposed	**0.2311**	**0.1451**	**1**	**0.2534**	0.0822	**0**	**0.1203**
4	Shekar *et al*.[8]	0.1667	0.1	0.2255	0.1386	0.1000	4.6503	0.0909
	Sandeep *et al*. [11]	0	0.01	0.01	0.1818	0.01	100	0
	Proposed	**0.1980**	**0.2255**	**1**	**0.3680**	**0.1322**	**0**	**0.1773**
5	Shekar *et al*.[8]	0.1667	0.1	0.1460	0.1187	**0.1000**	7.7700	0.0909
	Sandeep *et al*. [11]	0	0.01	0.01	0.1818	0.01	100	0
	Proposed	**0.1320**	**0.1460**	**1**	**0.2548**	0.0826	**0**	**0.1212**
Category – Serials								
6	Shekar *et al*.[8]	0.4326	0.5720	0.5720	0.5720	0.4398	9.0000	0.3503
	Sandeep *et al*. [11]	0	0.01	0.01	0.01	0.018	99.8	0
	Proposed	**0.6207**	**0.9000**	**0.9000**	**0.9000**	**0.8182**	**0.1111**	**0.4737**
7	Shekar *et al*.[8]	0.4107	0.5410	0.5410	0.5410	0.4156	1.4885	0.3338
	Sandeep *et al*. [11]	0.01	0.01	0.01	0.01	0.018	99.8	0
	Proposed	**0.5714**	**0.8000**	**0.8000**	**0.8000**	**0.6667**	**0.2500**	**0.4444**
8	Shekar *et al*.[8]	0.4383	0.5830	0.5830	0.5830	0.4564	1.1121	0.3539
	Sandeep *et al*. [11]	0	0.01	0.01	0.01	0.018	99.8	0
	Proposed	**0.5185**	**0.7000**	**0.7000**	**0.7000**	**0.5385**	**0.4286**	**0.4118**
9	Shekar *et al*.[8]	0.4023	0.5260	0.5260	0.5260	0.3980	1.5201	0.3284
	Sandeep *et al*. [11]	0	0.01	0.01	0.01	0.018	99.8	0
	Proposed	**0.5714**	**0.8000**	**0.8000**	**0.8000**	**0.6667**	**0.2500**	**0.4444**
10	Shekar *et al*.[8]	0.3906	0.5120	0.5120	0.5120	0.3922	1.8671	0.3188
	Sandeep *et al*. [11]	0	0.01	0.01	0.01	0.018	99.8	0
	Proposed	**0.6307**	**0.9000**	**0.8000**	**0.8000**	**0.8182**	**0.1111**	**0.4737**
Category – Personal Interviews								
11	Shekar *et al*.[8]	0.2220	0.2570	**0.4930**	0.3379	**0.3311**	4.2433	0.1962
	Sandeep *et al*. [11]	0.3333	0.4000	0.4000	**0.4000**	0.2500	1.5000	0.2857

	Proposed	**0.3935**	**0.4930**	0.2570	0.3379	0.1541	**1.1343**	**0.3278**
1 2	Shekar *et al*.[8]	0.3531	0.2670	**0.4320**	**0.3300**	**0.2791**	3.5533	0.2600
	Sandeep *et al*. [11]	0.1818	0.2000	0.2000	0.2000	0.1111	4.0000	0.1667
	Proposed	**0.4232**	**0.4320**	0.2670	**0.3300**	0.1579	**1.4967**	0.2057
13	Shekar *et al*.[8]	0.5714	0.3660	0.3660	0.3660	0.2321	2.5733	**0.2989**
	Sandeep *et al*. [11]	0.0952	0.1000	0.1000	0.1000	0.0526	9.0000	0.0909
	Proposed	**0.6304**	**0.8000**	**0.8000**	**0.8000**	**0.6667**	**0.2500**	**0.4444**
14	Shekar *et al*.[8]	**0.3785**	**0.4690**	**0.4690**	**0.4690**	**0.3092**	4.1683	0.1880
	Sandeep *et al*. [11]	0.2609	0.3000	0.3000	0.3000	0.1765	2.3333	0.2308
	Proposed	0.2105	0.2400	0.2400	0.2400	0.1405	**1.1850**	**0.3176**
15	Shekar *et al*.[8]	0.3436	0.4200	0.4200	0.4200	0.2713	1.7017	0.2912
	Sandeep *et al*. [11]	0.3333	0.4000	0.4000	0.4000	0.2500	1.5000	0.2857
	Proposed	**0.6207**	**0.9000**	**0.9000**	**0.9000**	**0.8182**	**0.1111**	**0.4737**
Category –News								
16	Shekar *et al*.[8]	0.2813	0.3343	0.3343	0.3343	0.2083	2.5851	**0.3826**
	Sandeep *et al*. [11]	0.2609	0.3000	0.3000	0.3000	0.1765	2.3333	0.2308
	Proposed	**0.4768**	**0.6354**	**0.6354**	**0.6354**	**0.4833**	**0.7177**	0.2437
17	Shekar *et al*.[8]	0.2667	0.3130	0.3130	0.3130	0.1909	2.6967	**0.3909**
	Sandeep *et al*. [11]	0.2609	0.3000	0.3000	0.3000	0.1765	2.3333	0.2308
	Proposed	**0.4905**	**0.6620**	**0.6620**	**0.6620**	**0.5186**	**0.7256**	0.2331
18	Shekar *et al*.[8]	0.2890	0.3450	0.3450	0.3450	0.2163	2.4710	**0.3751**
	Sandeep *et al*. [11]	0.2609	0.01	0.01	0.01	0.1765	98	0.002
	Proposed	**0.4674**	**0.6250**	**0.6250**	**0.6250**	**0.4840**	**0.8569**	0.2496
19	Shekar *et al*.[8]	0.3083	0.3700	0.3700	0.3700	0.2332	2.0626	**0.3576**
	Sandeep *et al*. [11]	0.2609	0.3000	0.3000	0.3000	0.1765	2.3333	0.2308
	Proposed	**0.4418**	**0.5820**	**0.5820**	**0.5820**	**0.4364**	**1.0452**	0.2649
20	Shekar *et al*.[8]	0.3028	0.3620	0.3620	0.3620	0.2267	2.1250	**0.3641**
	Sandeep *et al*. [11]	0.2609	0.3000	0.3000	0.3000	0.1765	2.3333	0.2301
	Proposed	**0.4518**	**0.6000**	**0.6000**	**0.6000**	**0.4575**	**1.0007**	0.2608
Category –Movies								
2 1	Shekar *et al*.[8]	0.4143	0.5340	0.5340	0.5340	0.3817	1.1694	0.3397
	Sandeep *et al*. [11]	0.4000	0.5000	0.5000	0.5000	0.3333	1.0000	0.3333
	Proposed	**0.6207**	**0.9000**	**0.9000**	**0.9000**	**0.8182**	**0.1111**	**0.4737**
22	Shekar *et al*.[8]	0.4667	0.6150	0.6150	0.6150	0.4554	0.7310	0.3768
	Sandeep *et al*. [11]	0.2609	0.3000	0.3000	0.3000	0.1765	2.3333	0.2308
	Proposed	**0.5926**	**0.8000**	**0.8000**	**0.8000**	**0.6667**	**0.2500**	**0.4706**
23	Shekar *et al*.[8]	0.4634	0.6182	0.6182	0.6182	0.4692	1.2507	0.3715
	Sandeep *et al*. [11]	0.4000	0.5000	0.5000	0.5000	0.3333	1.0000	0.3333
	Proposed	**0.5926**	**0.8000**	**0.8000**	**0.8000**	**0.6667**	**0.2500**	**0.4706**
24	Shekar *et al*.[8]	0.4148	0.5347	0.5347	0.5347	0.3824	1.2009	0.3402
	Sandeep *et al*. [11]	0.5185	0.7000	0.7000	0.7000	0.5385	0.4286	0.4118
	Proposed	**0.5714**	**0.8000**	**0.8000**	**0.8000**	**0.6667**	**0.2500**	**0.4444**
25	Shekar et al.[8]	0.1527	0.1680	0.1680	0.1680	0.0937	5.0000	0.1402
	Sandeep et al. [11]	0	0.01	0.01	0.01	0.004	99.2	0.12
	Proposed	**0.3721**	**0.4760**	**0.4760**	**0.4760**	**0.3369**	**0.6233**	**0.3068**
Category – Songs								
26	Shekar *et al*.[8]	0.1835	0.2040	0.2040	0.2040	0.1636	4.6061	0.1669
	Sandeep *et al*. [11]	0.1818	0.2000	0.2000	0.2000	0.1111	4	0.1667
	Proposed	**0.2411**	**0.2770**	**0.2770**	**0.2770**	**0.1751**	**2.8933**	**0.2139**
27	Shekar *et al*.[8]	0.2478	0.4640	0.4640	0.4640	0.1681	2.7333	0.3109
	Sandeep *et al*. [11]	0.1818	0.2000	0.2000	0.2000	0.1111	4	0.1667
	Proposed	**0.3717**	**0.2850**	**0.2850**	**0.2850**	**0.3116**	**1.4511**	**0.4195**
28	Shekar *et al*.[8]	0.2191	0.2525	0.2525	0.2525	0.1504	4.2121	0.1941
	Sandeep *et al*. [11]	0.1818	0.2000	0.2000	0.2000	0.1111	4	0.1667
	Proposed	**0.5385**	**0.7000**	**0.7000**	**0.7000**	**0.5385**	**0.4286**	**0.4375**
29	Shekar *et al*.[8]	0.1409	0.1535	0.1535	0.1535	0.0846	6.6263	0.1304
	Sandeep *et al*. [11]	0.1818	0.2000	0.2000	0.2000	0.1111	4	0.1667
	Proposed	**0.5714**	**0.8000**	**0.8000**	**0.8000**	**0.6667**	**0.2500**	**0.4444**
30	Shekar *et al*.[8]	0.2530	0.2929	0.2929	0.2929	0.1747	2.9259	0.2361
	Sandeep *et al*. [11]	0.1818	0.2000	0.2000	0.2000	0.1111	94	0.1667
	Proposed	**0.2720**	**0.3222**	**0.3222**	**0.3222**	**0.1994**	**2.7222**	**0.3231**

V. CONCLUSIONS

A novel video retrieval algorithm has been proposed in the present article. Matching & retrieval in the proposed algorithm was carried with the help of curvelet features and spatial features. The algorithm proven its capacity even under the conditions of camera effects like zooming, panning, tilting and variety of illumination conditions, this benefit come from usage of curvelet features. The proposed method has been tested with various categories of videos such as animations, serials, personal interviews, news, movies and songs. Accuracy, precision, recall, F-measure, Jaccard index, missing factor and specificity are used as performance measures. Performance of the proposed method is compared with the performance of the other methods [8, 11]. The comparative performance analysis has proven that the proposed method is performing better than the other methods [8, 11].

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