

An Effective Detection of Similar Video Streams Using DQO Techniques

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ABSTRACT

It is undesirable to manually check whether a video is part of a long stream by browsing its entire length. Video subsequence identification involves locating the position of the most similar part with respect to a user specified query clip Q from a long pre-stored video sequence S.

Data mining focuses on extracting useful information from large volumes of data, and thus has been the center of much attention in recent years. Building scalable, extensible, and easy-to-use data mining systems, however, has proved to be difficult. In this system, a framework is proposed to find the similar content of a short query clip from a long video sequence, with extension to identify the occurrence of potentially different ordering or length due to content editing using kNN- search, Maximum Size Matching (MSM) and Sub-Maximum Similarity Matching (SMSM) Algorithms.

Keywords: Video sequence, Dynamic query, Frames, Segment

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I. INTRODUCTION

It has been developed in order to detect videos which have the same content as a video query. These videos are spotted by considering the distance between the four centroids of the request and those of the videos analyzed, on 200 consecutive images. A good robustness to different transforms has also been observed, but a problem still remains concerning large logo superimposition(Hampapur et al).The signature of a frame is obtained by partitioning the image into blocks and extracting the local feature representing the dominant type of edge direction from each block.

The similarity between the signatures is calculated by comparing the edge types of the corresponding blocks, and counting the number of the blocks having the same edge type. It has been discussed the challenges of similarity search in large video databases(Hoad et al). The proliferation of digital video support the require of video copy detection for content and rights management. An efficient video copy detection technique should be able to deal with spatiotemporal variations (e.g., changes in brightness or frame rates), and lower down the computation cost. A time warping matching algorithm is used to deal with video temporal variations (Shao et al).

In existing system, manual checking and presegmentation was required while browsing the entire length video. Therefore the proposed system is designed to identify the relevant video, even if it exists some transformation distortion by using Dynamic query ordering(DQO).

II. VIDEO SUBSEQUENCE IDENTIFICATION

It is undesirable to manually check whether a video is part of a long stream by browsing its entire length, thus a reliable solution of automatically finding similar content is imperative. Retrieval job typically returns similar clips from a large collection of videos which have been either chopped up into similar lengths or cut at content boundaries.

Subsequence identification task intend to find out the presence of any subsequence long database video that shares similar content to a query clip. It doesn't involve pre segmentation of the video required by the proposals based on short boundary detection. It implements the spatial pruning to avoid seeking over the entire database sequence of feature vectors for exhaustive comparison. Different from copy detection which normally considers transformation distortions only, a visually similar video can be further relaxed to be changed with content editing at frame or shot level (swap, insertion, deletion or substitution), thus could lead to different ordering or length with original source.

III. METHODOLOGIES USED IN VIDEO SUBSEQUENCE IDENTIFICATION

The various algorithms used in this task are the following:

k-NN Search, Dense Segment Extract, Maximum Size Matching and Dynamic Query Ordering

3.1k-NN SEARCH

Similar frame retrieval in forged video sequence S for each element of Query clip Q is processed as a range or k NN search. Traditionally, frames are regarded as similar if their distance is under a threshold thus range search is often used. A necessary condition for a subsequence S to be similar to Q is they share sufficient number of similar frames. The parameter k in k NN search of similar frame retrieval affects the complexity, which in turn affects the number of segments, their lengths and densities. An increasing k makes the hit ratio of this method fluctuate and peak to 90% when k is around 500 and 1000. When k is too small, the number of edges will be small. For some queries, false discards could be incurred due to the potential inadequate recall of similar frames.

3.2DENSE SEGMENT EXTRACT

The novel batch query algorithm to reprocess the similar frames, the mapping relationship among the query and database video is first represented by a bipartite graph. The similar parts along the long sequence are then extracted, followed by a filter-and-refine search technique to reduce some unrelated subsequences. The dense segment extraction is a query-aware process, i.e., video segmentation is materialized on-the-fly. It is different from the offline pre-segmentation by detecting shot boundaries typically in video retrieval.

3.3MAXIMUM SIZE MATCHING

In the sorting stage, Maximum Size Matching (MSM) is set up for each sub graph built by the query and candidate subsequence to attain a smaller set of candidates. Sub-Maximum Similarity Matching (SMSM) discovered the subsequence with the highest summative score from all candidates, according to a the video similarity model that integrate Visual content, secular order and frame merger information.

3.4.DYNAMIC QUERY ORDERING

This Dynamic Query Ordering (DQO) algorithm introduced in can perform a number of individual k NN searches on a same dataset simultaneously, to significantly reduce the total number of page accesses and distance computations. The basic idea is that, since normally nearby feature vectors in a video are similar; some results of next query could be probably contained in the results of previous queries. Thus, the retrieval efficiency in searching large video databases can be improved greatly.

IV. SYSTEM MPLEMENTATION

The implementation of the proposed system is done in three modules such as Transformation & Normalization, Retrieval of similar frames, Computation.

In Transformation & Normalization, the most prominent visual feature – RGB color histogram, was extracted due to its computation efficiency. In general, color histograms are partially reliable even in the presence of variations in visual appearance, and provide useful clues for similarity of frames. Four feature datasets in 8-, 16-, 32- and 64-dimensional spaces were generated for each frame of this video, and the value of each dimension was normalized by dividing the total number of pixels.

In the Retrieval of similar frames, each query is a short video (varying from 5 to 50 seconds) taken from the test video recording, optionally edited with some change to make it have different ordering, length or content with the original extracted fragment (i.e., ground-truth).

Most of the time a query video is suggest to discover the starting and ending boundaries of its corresponding target subsequence in the database we do following process. Constructing a bipartite graph representing the similar frame mapping relationship between the original Query clip and the forged Test clip, with an efficient k NN search algorithm, all the possible similar video subsequences of the forged Test clip along the one dimensional temporal line can be extracted. It has been proposed a graph transformation and matching approach to process variable length comparison over database video with query through computation. It facilitates safely pruning a large portion of irrelevant parts and rapidly locating some promising candidates for further similarity evaluations.

The effective but still efficient identification of the most similar subsequence, the proposed query processing is conducted in a coarse-to-fine style. grand a one-to-one mapping constraint related in spirit to that of, Maximum Size Matching (MSM is employed to rapidly filter some actually non-similar subsequences with lower computational cost.

The smaller numbers of candidates which contain eligible numbers of similar frames are then further evaluated with relatively higher computational cost for accurate identification. Since measuring the video similarities for all the possible 1:1 mappings in a sub graph is computationally intractable, a heuristic method Sub-Maximum Similarity Matching (SMSM) is devised to quickly identify the subsequence corresponding to the most suitable 1:1 mapping.

4.1 CODING AND TESTING

4.1.1 CODING

Once the design aspect of the system is finalized, the system enters into the coding and testing phase. The coding part brings the definite system into action by converting the design of the system into the code in a given programming language. Therefore, a good coding style has to be taken whenever changes are required.

4.1.2 TESTING

Testing is performed to identify errors. It is used for quality assurance. Testing is an integral part of the entire development and maintenance process. The goal of the testing during phase is to verify that the specification has been accurately and completely incorporated into the design, as well as to ensure the correctness of the design itself. Testing checks for the errors, as a whole of the project testing involves the following test cases: Static analysis is used to investigate the structural properties of the Source code.

Dynamic testing is used to investigate the behavior of the source code by executing the program on the test data.

4.1.3 TEST CASES

The Table 1 shows some of the test cases of the proposed framework. Here the various error cases which will indicate the user to select correct file format, to upload all inputs are also shown. The snapshots depicted the error cases of the proposed framework

Table 1.

No of Test Cases	3
No of Test Case Passed	3
No of Test Cases Failed	0

V. RESULT AND DISCUSSION



Fig 1 Front Screen

Snapshot shown in the Fig 1, is the main screen, which have three input fields(select test file,select query file and match count.

5.1 Test case 1

System displays an Error Message when file type other than MPEG is selected. selecting a file other than mpeg is shown in Fig 2



Fig 2 Selecting a file other than MPEG

The snap shot shown in the Fig 2, a database file is selected as an input Test file to test the Error Case. After the test, the error message is displayed in fig 3



Fig 3 Displaying an Error Message

In, the Error Message snap shot, the Error Message is displayed as “Select movie file” when the user selects a file other than MPEG as Test file.

5.2 Test case 2

In this case, normally System should display an Error Message when the search icon is clicked without selecting any one of the inputs the Query file or the Test file or without entering the match count. But it is implemented that System displays an Error Message when the search icon is clicked without selecting any one of the inputs or without entering the Match Count.



Fig 4 Displaying an alert message

The snapshot shown in Fig 4, displays the Error Message is displayed as “Select Clips and Counts first” when the search icon is clicked without selecting any of the inputs or without entering the Match Count.



Fig 5 Uploading video file

The snapshot shown in fig 5, displays the Uploading of both Test file and query file in MPEG format.

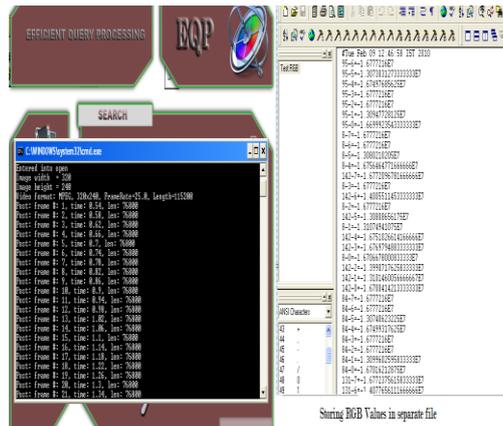


Fig 6 Processing of the inputs

During execution, RGB values is stored in separate file. The Snapshot fig 6, displays the Storing of RGB values.



Fig 8 Final Output

The snapshot shown in the fig 8 ,displays the output.

VI. CONCLUSION

This framework presented effective and proficient query processing approach for secular localization of similar content from a long unsegmented video stream, considering target subsequence may be approximate occurrence of potentially different length with query clip. In practice, visually similar videos may exhibit with different orderings due to content editing, which yields some intrinsic cross mappings. This approach does not involve the pre-segmentation of video required by the proposals based on shot boundary detection. The advantage of this method is that, it is not only based on average distance of frame pairs to capture visual content, but also well considers temporal order and frame alignment. Video subsequence identification involves locating the position of the most similar part with respect to a user specified query clip Q from a long pre-stored video sequence S where the test video and query clips are MPEG and JPEG images respective.

Hence, in order to compute the similarity between various video formats other than MPEG...the system can be further enhanced to determine a new proactive approach to obtain maximum efficiency and effectiveness.

REFERENCES

- [1]. A. Hampapur, K.-H. Hyun, and R.M. Bolle, "Comparison of Sequence Matching Techniques for Video Copy Detection," Proc. Storage and Retrieval for Image and Video Databases (SPIE '02), pp. 194-201, 2002.
- [2]. T.C. Hoad and J. Zobel, "Detection of Video Sequences Using Compact Signatures," ACM Trans. Information Systems, vol. 24, no. 1, pp. 1-50, 2006.
- [3]. J. Shao, Z. Huang, H.T. Shen, X. Zhou, E.-P. Lim, and Y. Li, "Batch Nearest Neighbor Search for Video Retrieval," IEEE Trans. Multimedia, vol. 10, no. 3, pp. 409-420, 2008.
- [4]. J. Yuan, L.-Y. Duan, Q. Tian, S. Ranganath, and C. Xu, "Fast and Robust Short Video Clip Search for Copy Detection," Proc. Fifth IEEE Pacific-Rim Conf. Multimedia (PCM '04), vol. 2, pp. 479-488, 2004.
- [5]. J. Han, M. Kamber, "Data Mining: Concepts and Techniques", Harcourt India / Morgan Kauffman, 2001.
- [6]. S.C.S. Cheung and A. Zakhor, "Efficient Video Similarity Measurement with Video Signature," IEEE Trans. Circuits and Systems for Video Technology, vol. 13, no. 1, pp. 59-74, 2003.

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