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AN EFFICIENT CONTENT AND SEGMENTATION BASED VIDEO COPY DETECTION

N. Kalaiselvi, K.Priyadharsan

[1]Department of Information Technology, Sri Manakula Vinayagar Engineering College, Puducherry, India
[2]Department of Computer Science and Engineering, Bharathiyar College of Engineering and Technology, karaikal/Pondicherry University, India

Abstract: The field of multimedia technology has become easier to store, creation and access large amount of video data. This technology has editing and duplication of video data that will cause to violation of digital rights. So in this project we implemented an efficient content and segmentation based video copy detection concept to detect the illegal manipulation of video. In this Work or proposed system, Instead of SIFT matching algorithms, used combination of SIFT and SURF matching algorithms to detect the matching features in images. Because, SIFT is slow and not good at illumination changes, while it is invariant to rotation, scale changes and affine transformations and then SURF is fast and has good performance, but it is also have some issues that it is not stable to rotation and affine transformations. So combined the above two algorithms SIFT and SURF to extract the image features. Auto dual Threshold method is used to segment the video into segments and extract key frames from each segment and it also eliminate the redundant frame. SIFT and SURF features based on SVD is used to compare the two frames features sets points, where the SIFT and SURF features are extracted from the key frames of the segments. Graph-based video sequence matching method is used to match the sequence of query video and train video. It skillfully converts the video sequence matching result to a matching result graph.

Keywords: Transformation, encoding, matching content

I. INTRODUCTION

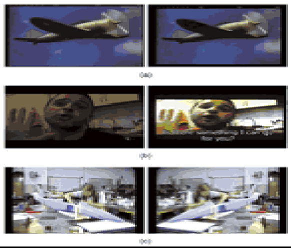
The objective of video copy detection is to decide whether a query video segment is a copy of a video from the video data set. This problem has received increasing attention in recent years; due to major copyright issues resulting from the wide spread use of peer-to-peer software and users uploading video content on online sharing sites such as YouTube and Daily Motion. As a consequence, an efficient and effective method for video copy detection has become more and more important.

Definition of Copy Video: Query video may be distorted in various ways. Such distortions include scaling, compression, cropping and cam-cording. If the system finds a matching video segment, it returns the name of the database video and the time stamp at which the query was copied.

In content-based video copy detection task so many transformations are defined. Some of the transformations like cam-coding; picture in picture; insertions of pattern: different patterns are inserted randomly: captions, subtitles, logo, sliding captions; strong re-encoding; change of gamma; Decrease in quality: Blur, change of gamma, frame dropping, contrast, compression,ratio, white noise; post production: crop, shift, contrast, caption(text insertion) flip (vertical mirroring), insertion of pattern, picture in picture(the original video is in the background).

As a consequence, an effective and efficient method for video copy detection has become more and more important. A valid video copy detection method is based on the fact that “video itself is watermark” and makes full use of the video content to detect copies.

TABLE I
Examples of some transformations

Example	Transformation
	Example of Decrease in quality: blur effect applied in image.
	Example Of cam-cording transformations which is done manually by filming a movie on a screen.
	Example of decrease in quality: change of gamma which means the gamma value for each color is changed randomly.

In the above all transformations, picture in picture is especially difficult to be detected. To detecting this kind of video copies, local features of SURF is normally valid. However, matching based on local features of each frames in two videos is in high computational complexity. In this paper, we focus on detecting picture in picture and propose a dual threshold method for video segmentation, feature set matching, and graph- based sequence matching method.

II. FRAMEWORK

The framework of an efficient content and segmentation based video copy detection is shown below:

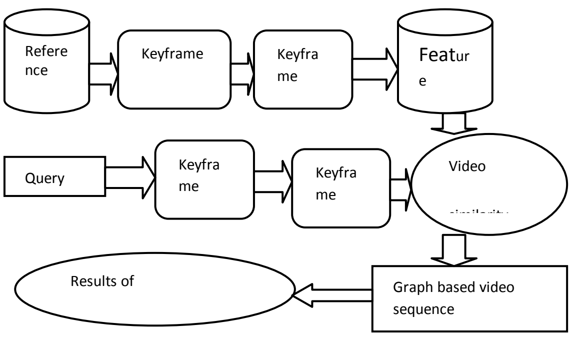


Fig. 1 A framework of an efficient content and segmentation based video copy detection.

This above process for an effective analysis of content based video copy detection is composed of two parts:

1. An offline step: Key frames are extracted from the reference video database and features are extracted from these key frames. The extracted features should be robust and effective to transformations by which the video may undergo. Also, the features can be stored in an indexing structure to make similarity comparison efficient.
2. An Online step: Query videos are analyzed. Features are extracted from these videos and compared to those stored in the reference database. The matching results are then analyzed and the detection results are returned.

III. RELATED WORK

AUTO DUAL-THRESHOLD METHOD

Auto dual-threshold method is mainly used to eliminate the redundant video frames. Normally, visual information of video frames is temporally redundant. So, video sequence matching is not necessarily to be carried out using all the video frames. An effective way of reducing non necessary matching is to extract certain key frames to represent the video content. And the matching of two video sequences can be first performed by matching the key frames.

By using the auto dual-threshold method segmenting method, continuous video frames can be segmented into temporally continuous and visually similar video segments. Three frames are extracted from each video segment, which are the first frame, the key frame and the last frame of this segment.

The key frame is determined by the frame that is the most similar to the average frame (that is the average feature value of all the frames within the segment). The key frame is used for video sequence matching, while the first and the last frames for accurately determining the segment location for copy detection and assisting matching. Each segment is assigned a continuous ID number along the time direction. We also make the statistical analysis on the time length of the video segments obtained by the auto dual-threshold method.

Our method aims to eliminate the near-duplicate frames along the video time direction; it does not take into account the concept of the shot, also does not require post processing to obtain the actual shots. Therefore, the particle size of our segmentation results is smaller than the shot, and is continuous in time, unlike the shot concept, but is sub shots or segments.

IV. MATCHING CONTENT FEATURE OF VIDEO USING SURF POINT DESCRIPTOR.

To better represent the local content of video frames, we choose SIFT and SURF(Speeded Up Robust Features) descriptors to present the video sequences. The following is the methodology of SURF.

DESCRIPTION

- Split the interest region up into 4 x 4 square sub-regions with 5 x 5 regularly spaced sample points inside
- Calculate Haar wavelet response d_x and d_y
- Weight the response with a Gaussian kernel centered at the interest point
- Sum the response over each sub-region for d_x and d_y separately → **feature vector of length 32**
- In order to bring in information about the polarity of the intensity changes, extract the sum of absolute value of the responses → **feature vector of length 64**
- Normalize the vector into unit length
- SURF-128-The sum of d_x and $|d_x|$ are computed separately for $d_y< 0$ and $d_y>0$
- Similarly for the sum of d_y and $|d_y|$
- This doubles the length of a feature vector.

MATCHING

- Fast indexing through the sign of the Laplacian for the underlying interest point
  - The sign of trace of the Hessian matrix
  - Trace = $L_{xx} + L_{yy}$
- Either 0 or 1 (Hard thresholding, may have boundary effect …)
- In the matching stage, compare features if they have the same type of contrast (sign)

V. GRAPH-BASED VIDEO SEQUENCE MATCHING METHOD

Video has inherent temporal characteristics that can also be used for video copy detection. In this paper, we propose a new graph based video sequence matching method that reasonably utilizes the videos temporal characteristics. This section will describe the proposed graph based video sequence matching method for video copy detection. The method is presented as follows:

Step1: segment the video frames and extract features of the key frames.

- Auto dual-threshold method used to segment the video sequences, and then extract SURF and SIFT features of the key frames.

Step 2: match the query video and target video.

Assume

- $Q_c = \{C_1^Q, C_2^Q, C_3^Q, \ldots.. C_m^Q\}$ and $T_c = \{C_1^T, C_2^T, C_3^T, \ldots.. C_m^T\}$ are the segment sets of the query video and target video from Step 1, respectively.
- For each C_i^Q in the query video, compute the similarity sim (C_i^Q, C_j^T) and return k largest matching results.
- K=∞n, where n is the number of segments in the target set, and ∞ is set to 0.05 based on our empirical study.

Step 3: generate the matching result graph according to the matching results.

- In the matching result graph, the vertex Mij represents a match between C_i^Q ,and C_j^T .
- To determine whether there exists an edge between two vertexes, two measures are evaluated.
- **Time direction consistency**: For M_{ij} and M_{lm}, if there exists $(i-l)*(j-m) > 0$, then M_{ij} and M_{lm} satisfy the time direction consistency.
- **Time jump degree:** For M_{ij} and M_{lm}, the time jump degree between them is defined as

$$\Delta t^{ij}_{lm=}\max(|\ t_i-t_l\ |,\ |\ t_j-t_m\ |\ )$$

Step 4: search the longest path in the matching result graph.

- The problem of searching copy video sequences is now converted into a problem of searching some longest paths in the matching result graph.
- The dynamic programming method is used in this paper. The method can search the longest path between two arbitrary vertexes in the matching result graph.

- These longest paths can determine not only the location of the video copies but also the time length of the video copies.

Step 5: output the result of detection.

- We can get some discrete paths from the matching result graph; it is thus easy to detect more than one copy segments by using this method.

VI. CONCLUSION

In this research propose a framework for content-based copy detection and video similarity detection. This paper first analyzes the features used for video copy detection.Based on the analysis, we use local feature derived by SIFT-SURF matching algorithms to describe video frames.Then, we use a dual-threshold method to eliminate redundant video frames and use the SIFT-SURF matching algorithm to compute the similarity of two SIFT-SURF feature point sets.Furthermore, for video sequence matching, we propose a graph-based video sequence matching method. It skillfully converts the video sequence matching result to a matching result graph.Thus, detecting the copy video becomes finding the longest path in the matching result graph.

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