

Abstract

Simple and robust local powerful descriptor called Weber Local Descriptor (WLD), which is put forward for detecting duplicated videos. Matching based on orthogonal moments has high computational complexity, especially for high dimension. Thus, to reduce the time complexity video is segmented into frame by twin threshold segmentation and key frames are extracted from each segment. Then, WLD descriptor is incorporated for feature extraction from each frame. Specifically, WLD consist of two components one is excitation and other is orientation. We use both these components to construct WLD histogram feature. Finally matching takes place between the features extracted from the reference video and the target video to check whether it is a duplicated or original video. The proposed method is more powerful to different noises, photometric and geometric transformations in the frame and detect the copied videos effectively with less computational complexity.

Keywords: Copied video detection, SIFT descriptor, Orthogonal moments, Keyframe, Dual threshold segmentation, transformations.

Introduction

With the rapid improvement of multimedia technologies, the cost of image, video data collection, creation of frames, and storage is becoming increasingly low. Every day hundreds of thousands of videos are created or generated and published. Among these huge volumes of videos or images there exist the large numbers of copies or near-duplicate videos. As a significance, an effective and efficient method for video copy detection has become more and more important. The intention of detecting copied video is to decide whether a query video segment is a copy of a video from the video database. A copy may have the impact of various transformations like cam-cording, picture in picture, crop, shift, contrast, blur, change of gamma. Fig. 1 shows the framework of content-based video copy detection framework. It is composed of two parts:

1) An offline step. Keyframes are extricated from the reference video database and features are extracted from these frame keywords. The medium along with extracted features should be robust and effective to transformations by which the video or sequence may undergo through this. Also, the features and frames can be stored in an indexing structure to make similarity comparison efficient.

2) An online step. Features are extracted from the target videos and compared to those stored in the referenced database with similar

search. Hence, the matching results are then analyzed and the detection results are returned.

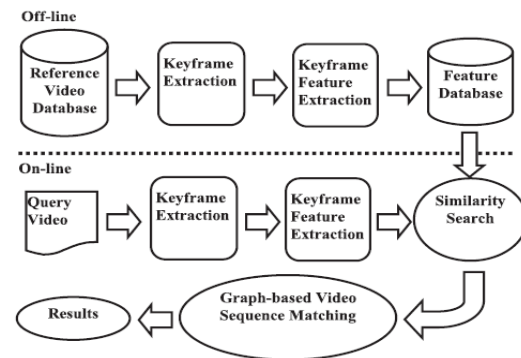


Fig.1 Framework of video copy detection.

Auto dual-Threshold Method

Auto dual-threshold method is used to drop unwanted excessive video frames. This methodology segments the continuous video frames into video segments by excluding temporal redundancy of the visual information. This method has two main characteristics. First, two thresholds are used. Specially, one threshold for detecting abrupt changes of visual information of frames and another threshold for gradual changes.

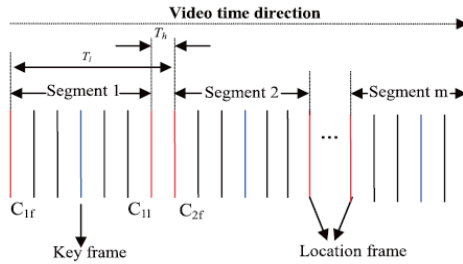


Fig.2 Auto dual-threshold method.

Second, two thresholds values are calculated adaptively according to video content. particularly, the higher threshold $T_h = \mu + \alpha\sigma$, where μ and σ are the mean and standard deviation of values between contiguous frames and α is suggested to be between 5 and 6 according to empirical study. The low threshold T_l is fixed to be $b \times T_h$, where b is selected from the range of 0.1-0.5. Then the auto dual-threshold method to eliminate the redundant frames is shown in Fig.2.

From each video segment three frames are extracted, they are the first frame, the keyframe and the last frame of this segment. For video sequence matching the keyframe is used, where the first and the last frames are used for finding out the segment location for copy detection and matching. Each segment is designated a continuous ID number along the time direction. Fig.3 shows an example video segmented by using auto dual-threshold method. For example, A Shot as shown in the figure, and also it can be further segmented throughout into m Segments by the auto dual-threshold method.

Weber Local Descriptor (WLD)

Weber Local Descriptor (WLD) is simple, very powerful and robust local descriptor. It is based on Weber’s law, states the fact that human perception of a pattern depends on not only the change of a stimulus but also the original intensity of the stimulus. Particularly, WLD contains two components: its differential excitation and its orientation. Differential excitation is a function of the ratio between the relative intensity differences of its neighbors against a current pixel and the intensity of the current pixel. An orientation is the action of orientating current pixel relative to certain positions. For a given image, we use the differential excitation and the orientation components to construct a concatenated WLD histogram feature.

Weber's Law

Weber’s law states that the ratio of the increment threshold to the background intensity is a constant. This relationship, known since as Weber’s Law, and it can be expressed as,

$$\frac{\Delta I}{I} = K \tag{1}$$

where ΔI represents the increment threshold (just noticeable difference for discrimination), I represents the initial stimulus intensity and k signifies that the proportion on the left side of the equation remains constant despite of variations in the I term. The fraction $\Delta I/I$ is known as the Weber fraction.

Differential excitation

Differential excitation is the intensity differences between its neighbors and a current pixel as the changes of the current pixel. Specifically, a differential excitation $\varepsilon(I_c)$ of a current pixel is computed as follows, where I_c denotes the intensity of the current pixel; I_i ($i=0, 1, \dots, p-1$) denote the intensities of p neighbors of I_c ($p=8$ here).

$$\begin{matrix} I_0 & I_1 & I_2 \\ I_7 & I_c & I_3 \\ I_6 & I_5 & I_4 \end{matrix} \xrightarrow{WLD(s,D)} \begin{cases} \varepsilon(I_c) = \arctan \left[\sum_{i=0}^{p-1} \left(\frac{I_i - I_c}{I_c} \right) \right] \\ \theta(I_c) = \arctan \left(\frac{I_{R(\delta+4)} - I_j}{I_{R(\delta+6)} - I_{R(\delta+2)}} \right) \end{cases} \tag{2}$$

Where, $R(x) = \text{mod}(x, p)$

To compute $\varepsilon(I_c)$, first calculate the differences between its neighbors and a center point:

$$f_{diff}(I_i) = \Delta I_i = I_i - I_c \tag{3}$$

By Weber’s law

$$f_{ratio}(\Delta I_i) = \frac{\Delta I_i}{I_c} \tag{4}$$

Subsequently, we consider the neighbor effects on the current point using a sum of the difference ratios:

$$f_{sum} \left(\frac{\Delta I_i}{I_c} \right) = \sum_{i=0}^{p-1} \left(\frac{\Delta I_i}{I_c} \right) \tag{5}$$

To increase the powerfulness of a WLD to noise, arctangent function is used as a filter on $f_{sum}(\cdot)$.

$$f_{arctan} \left[\sum_{i=0}^{p-1} \left(\frac{I_i - I_c}{I_c} \right) \right] = \arctan \left[\sum_{i=0}^{p-1} \left(\frac{I_i - I_c}{I_c} \right) \right] \tag{6}$$

So, $\varepsilon(I_c)$ is computed as:

$$\varepsilon(I_c) = \arctan \left[\sum_{i=0}^{p-1} \left(\frac{I_i - I_c}{I_c} \right) \right] \tag{7}$$

Note that $\varepsilon(I_c)$ may take a minus value if the intensities of neighbors are smaller than that of a current pixel. Intuitively, if $\varepsilon(I_c)$ is positive, it simulates the case that the surroundings is lighter than the current pixel. In contrast, if $\varepsilon(I_c)$ is negative, it simulates the case that the surroundings is darker than the current pixel. By this means, we attempt to preserve more discriminating information in comparison to using the absolute value of $\varepsilon(I_c)$.

Orientation

For the orientation component of WLD, it is calculated as:

$$\theta(I_c) = \arctan\left(\frac{I_{R(i+4)} - I_i}{I_{R(i+6)} - I_{R(i+2)}}\right) \quad (8)$$

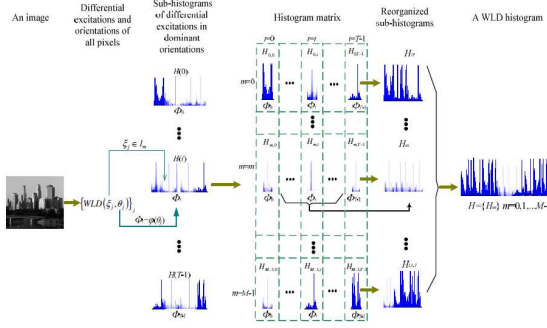
where $I_i (i=0,1,\dots,p/2-1)$ are the neighbors of a current pixel, p is the number of neighbors, $R(x)$ is to perform the modulus operation, i.e., $R(x)=\text{mod}(x,p)$

The quantization function is as follows:

$$\varphi(\theta) = \frac{2t}{T}\pi, \text{ and } t = \text{mod}\left[\left[\frac{\theta}{2\pi/T} + \frac{1}{2}\right], T\right] \quad (9)$$

WLD histogram

The WLD features for each pixel are computed and encoded into a histogram H . The differential excitations are then grouped as T sub-histograms $H(t)$ ($t=0, 1, \dots, T-1$), each sub-histogram $H(t)$ corresponding to a dominant orientation. Subsequently, each sub-histogram $H(t)$ is evenly divided into M segments. Furthermore, a segment Hm, t is composed of S bins, i.e., $Hm, t = \{hm, t, s\}, s=0, 1, \dots, S-1$



3. An illustration of WLD histogram for a given Image

Graph Based video sequence matching Method for Videocopy Detection

A new graph-based video sequence matching method that make use of the video's temporal characteristics to solve the problem of the efficiency of video copy detection. Then the proposed graph-based video sequence matching method for video copy detection is presented as follows:

Step 1: Videos are segmented into the video frames and features are extracted from the keyframes. According to the method described in Section 2, we perform the dual threshold technique to segment the video sequences, and then extract SIFT features of the keyframes.

Step 2: Query video and target video are matched. Assume that $Q_C = \{c_1^Q, c_2^Q, \dots, c_m^Q\}$ and $T_C = \{c_1^T, c_2^T, \dots, c_n^T\}$ are the segments sets of the query video and target video from step 1.

Step 3: Generate the matching result graph according to the matching results. The vertex M_{ij}

represent the match between c_i^Q and c_j^T . To find out whether there exists an edge between two vertices, two calculations are performed.

Time direction consistency: For M_{ij} and M_{lm} , if there exists $(i-1)*(j-m)$ 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

$$\Delta t_{lm}^{ij} = \max(|t_i - t_l|, |t_j - t_m|) \quad (10)$$

There exists an edge between two vertices, if the following two requirements are satisfied:

1. The two vertices should meet time direction compatibility.
2. The time jump degree

Requirement 1 indicates that the video subsequent temporal order between the target video and query video must be consistent. If Requirement 1 is met, Requirement 2 is used to constrain the time span of two matching results between the query video and the target video. Even though the time span exceeds a certain threshold, also it is considered that there does not exist certain correlation between the two matching results.

Step 4: To find the longest path in the matching result graph. Searching for the longest paths in the matching result graph is the problem. These longest paths can find out not only the location of the video copies but also the time length of the video copies. The method can search the longest path between two arbitrary vertices in the matching result graph.

Step 5: Output the result of detection. If it has more than one path or no path, for each vertex of the matching result graph. As in Fig. 5, for the vertices $M_{1;29}, M_{1;76}$, and $M_{2;76}$, they have no path to other vertices. For $M_{1;26}$, four paths are available. Accordingly, we can get some discrete paths from the matching result graph, thus easy to detect more than one copy segments by using this technique

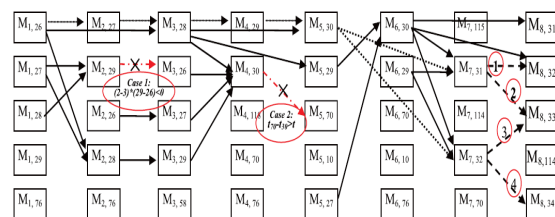


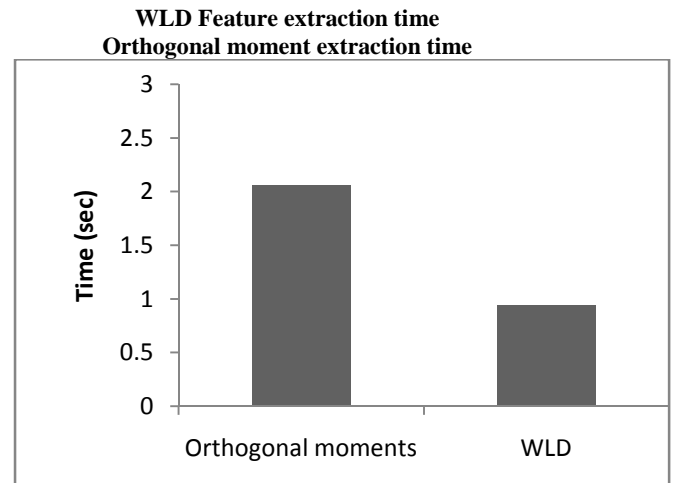
Fig.4 Matching results between query video and target video.

Results

The purpose of this study is to detect the copy videos in large video data set. In this test, we compare the proposed approach with orthogonal moments. We compare the time complexity and accuracy of our proposed Weber's Local Descriptor with the existing method. The time complexity is low in the proposed method because all

the operations involved is only addition, which consumes less time where the operations involved in orthogonal moment is multiplication which consumes more time. The number of features extracted in WLD is high, hence automatically the accuracy of copy detection is high in WLD compare to orthogonal moment.

No of Frames	No of Key frames	keyframe detection	No of Features	Feature extraction
120	11	0.025s	[11 x 3 x 360]	0.94s
119	11	0.006s	[11 x 3 x 360]	0.88s
119	10	0.003s	[11 x 3 x 360]	0.79s
No of Frames	No of Key frame	keyframe detection	No of Features	Feature extraction
120	11	0.025s	[11 x 3 x 256]	2.06s
119	11	0.006s	[11 x 3 x 256]	1.98s
119	10	0.003s	[11 x 3 x 256]	1.81s



7. Time complexity comparison

Conclusion

WLD based video sequence matching method can be used efficiently for detecting the copied video. Since, matching based on orthogonal moment descriptor has high computational complexity. Thus, to reduce the time complexity video is segmented into frame by Twin threshold segmentation and key frames are extracted from each segment. Then, WLD descriptor is incorporated for feature extraction from each frame. Finally matching takes place between the features extracted from the reference video and the target video to check whether it is a original video or duplicated video. Experimental results also shows this method can be used efficiently for detecting the copied video with less computational complexity.

References

- [1] Jie Chen, Shinguang Shan, Guoying Zhao, "WLD: A Robust Local Image Descriptor", *IEEE Transaction on pattern analysis and intelligence*, Vol.32, no.9, September 2010.
- [2] X.Wu, C.-W. Ngo, A.Hauptmann, and H.-K. Tan, "Real-Time Near-Duplicate Elimination for Web Video Search with Content and Context", *IEEE Trans. Multimedia*, vol.11, no.2, p. 196-207, Feb.2009.
- [3] *TRECVID 2008 Final List of Transformations*, <http://www.nlpir.nist.gov/projects/tv2008/active/cy.detection/final.cbcd.video.transformations.pdf>, 2008.
- [4] *Final CBCD Evaluation Plan TRECVID 2008 (v1.3)*, <http://www.nlpir.nist.gov/projects/tv2008/Evaluation-cbcd-v1.3.htm>, 2008.
- [5] O.Küçükçuntunc, M.Bastan, U.Güdükbay, and Ö.Ulusoy, "Video Copy Detection Using Multiple Visual Cues and MPEG-7 Descriptors," *J. Visual Comm. Image Representation*, vol. 21, pp. 838-849, 2010.
- [6] M. Douze, H. Jegou, and C. Schmid, "An Image-Based Approach to Video Copy Detection with Spatio-Temporal Post-Filtering," *IEEE Trans. Multimedia*, vol. 12, no. 4, pp. 257-266, June 2010.
- [7] M. Douze, A. Gaidon, H. Jegou, M. Marszalek, and C. Schmid, *TREC Video Retrieval Evaluation Notebook Papers and Slides: INRIA-LEAR's Video Copy Detection System*, <http://www.nlpir.nist.gov/projects/tvpubs/tv8.papers/inria-lear.pdf>, 2008.
- [8] A.Hampapur and R.Bolle, "Comparison of Distance Measures for Video Copy Detection," *Proc. IEEE Int'l Conf. Multimedia and Expo (ICME)*, pp. 188-192, 2001.