A Near-Duplicate Video Retrieval Method Based on Zernike Moments

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ABSTRACT

In this paper, a near-duplicate video retrieval method developed based on invariant features was proposed. After shot change detection, Zernike moments are extracted from each key-frame of videos as invariant features. We obtain the key-frame similarity by computing the difference of Zernike moments between key-frames of the query and test videos. To achieve near-duplicate video retrieval, each key-frame is considered as an individual sensor and then evaluating all of key-frames is considered as multiple sensors. The results of key-frames are fused to obtain a better performance of near-duplicate video retrieval. The experimental results show that the proposed method can not only find the relevant videos effectively but also resist to the possible modifications such as re-scaling and logo insertion.

Keywords: near-duplicate video retrieval, Zernike moments, big data;

1. INTRODUCTION

Due to remarkable advance of communication technology, the growth of online videos is huge in past few years. According to the report on the official YouTube website, there are more than 1 billion users and 300 hours of videos are uploaded to YouTube every minute. This means that how to manage the video content effectively becomes increasingly important. Therefore, some emerging services such as video sharing, video broadcasting, and video recommendation draw researchers’ attention.

As for video sharing, most websites often allow their users to freely upload videos without any checking procedures. It is expected that some videos with the same or similar content can be found on Internet. Figure 1 illustrates these some cases of near-duplicate videos. Figure 1(a) is an original frame and Fig. 1(b), 1(c), 1(d) are three common duplicates of Fig. 1(a). These videos with similar content are called as near-duplicate videos (NDVs). To improve the efficiency of video management, it is an important issue to retrieve and manage these near-duplicate videos. The technique that retrieves near-duplicate videos is called Near-Duplicate Video Retrieval (NDVR). Though there are some existing methods [1-3], developing an efficient NDVR method is still challenging. Therefore, we aim at developing an effectively NDVR method.

Fig. 1 Samples of near-duplicate videos: (a) original (b) rescaling (c) mirroring, and (d) logo insertion

2. Related Work

NDVR often contains three parts: video signature, similarity measure, and searching algorithm. Based on [2], existing video signatures can be classified into several classes according to what kinds of information are adopted.

The video-level global signature translates whole video into single signature. In [3], Huang et al. introduced a statistical model called Bounded Coordinate System (BCS). By combining the principal component analysis (PCA) and the Bi-distance Transformation (BDT), a video clip can be summarized as a coordinate system which records the dominating content-changing trends
and ranges by directions and lengths. Since global signature is very compact, it usually reduces the content redundancy to bring various benefits in storage, management, computation, and retrieval. However, it ignores the local information like the object or region in video easily and exist doubt of representativeness.

Frame-level local signature extracts the local feature on individual frame like local key-point descriptors. Such usage in NDVR is closely related to near-duplicate image retrieval like [4]. Due to the higher computationally then video-level global feature, there exists two classes of frame level local signature usage. One of them is doing pairwise frame matching with local key-point descriptors. It costs lots of computation and need acceleration like pre-filtering.

To improve the time complexity issue of frame-level local signature, more studies tend to transform the local information into global signature. The Bag of Words (BoW) model is often applied for image classification in computer vision [5]. It seems the image as a document and the key-point descriptors are the words in the document. To convert the local descriptors of image into the visual words, each descriptor will be matched with "codebook" which has been trained by clustering algorithm like k-means clustering. A frame can be represented as a histogram of the occurrences of the visual words in that frame. The BoW model shows excellent precision and high efficiency in NDVR [6].

Spatio-temporal signature represents not only the frame information, but also the change between frames. Zobel and Hoad [7] used the shot information to represent the frame signature. It summarizes a video into a sequence of numbers, each representing a shot length, the change of color distribution between frames and the inter-frame change in spatial movement of the lightest and darkest pixels in each frame over time. However, all the codes only indicate the consecutive inter-frame difference within each individual sequence without carrying content information. Huang et al. [8] proposed a method which transforms a video stream into the one-dimensional Video Distance Trajectory (VDT), which preserves some content information due to the usage of the reference point. The difference of color histogram between frames will be calculated, and converted into a sequence of compact signatures called Linear Smoothing Functions (LSFs). LSF adopts compound probability to combine three independent video factors for effective segment similarity measure, which is then utilized to compute sequence similarity for NDVR.

Though the SIFT features are useful to find the corresponding frames, their computational complexity is too much and then limit their applicability of real applications. On the other hand, some modifications such as cropping and mirror reflection may be used to generate near-duplicate videos. Therefore, invariant features are necessary and important to develop an effective NDVR method.

3. Proposed Method

Image moments are scale invariant and have been used in many applications such as image retrieval [9],[11]. One important advantage of Zernike moments [10] is resistant to geometric rotation and noise. It is expected that this property of Zernike moments is useful for near-duplicate video retrieval. On the other hand, it is no doubt that the computational complexity of processing all of frames in a video is very high. To reduce the computational complexity, we only extract and examine the key-frames. Therefore, it motivates us to develop an efficient NDVR method based on Zernike moments. Figure 2 illustrate the proposed NDVR method.

Let an original video sequence be \( I^o \) and there are some key-frames \( I^K_o \). A near-duplicate video sequence \( I^c \) with the same frame dimensions as \( I^o \) and there are some key-frames \( I^K_c \). Similar to [12], we extract a set of features from \( I^K_o \) and another set from \( I^K_c \). Then, the similarity between \( I^K_o \) and \( I^K_c \) is measured by computing the distance between their features.

\[
\phi_i = \sum x \sum y (x - \bar{x})(y - \bar{y}) f(x, y)
\]  

Fig. 2 Block diagram of the proposed NDVR method

3.1 Global Invariant Moment

Since the frame size may not be the same, we normalize the frames of the original video and the near-duplicate version before computing the Zernike moments. After normalization, we measure a Sobel edge map of each key-frame and then the edge map is used for computing Zernike moments.

First, we describe the \((i+j)\)-order central moments as follows:

\[
\phi = \sum x \sum y (x - \bar{x})(y - \bar{y}) f(x, y)
\]
where \( f(x, y) \) denotes the edge map and \( \bar{f}(x, y) \)
represents the centroid of the edge points. Then the
moment \( \varphi_i \) can be expressed as follows:
\[
\varphi_i = \frac{\varphi_i^{(0,0)}}{\varphi_{00}^{(0,0)}}
\]
(2)

Based on Eq. (2), six invariant moment \( M_i \) \((i=1,2,,6)\)
can be expressed in the following:
\[
M_1 = \frac{3}{\pi} (\varphi_{20} + \varphi_{02} - 1)
\]
(3)
\[
M_2 = \frac{9}{\pi} [(\varphi_{20} - \varphi_{02})^2 + 4\varphi_{11}^2]
\]
(4)
\[
M_3 = \frac{16}{\pi} [(\varphi_{30} - 3\varphi_{12})^2 + (3\varphi_{31} - \varphi_{03})^2]
\]
(5)
\[
M_4 = \frac{144}{\pi} [(\varphi_{30} + \varphi_{12})^2 + (\varphi_{21} + \varphi_{03})^2]
\]
(6)
\[
M_5 = \frac{13824}{\pi} [((\varphi_{30} - 3\varphi_{12})(\varphi_{30} + \varphi_{12})^2 - 3(\varphi_{30} + \varphi_{12})^2]
\]
\[
+ (3\varphi_{30} - \varphi_{31})(\varphi_{30} + \varphi_{31})^2]
\]
\[
+ (3\varphi_{30} - \varphi_{31})(\varphi_{30} + \varphi_{31})]^2
\]
(7)
\[
M_6 = \frac{864}{\pi} [(\varphi_{20} - \varphi_{02})^2 (\varphi_{30} + \varphi_{12})^2 - (\varphi_{30} + \varphi_{12})^2]
\]
(8)
\[
+ 4\varphi_{12}(\varphi_{30} + \varphi_{12})(\varphi_{30} + \varphi_{12})]
\]

According to Eqs. (3) to (8), six Zernike moments can
be computed and then formed as a feature vector.

3.2 Similarity measurement

After measuring Zernike moments of each key-frame,
we need to measure the similarity of two videos.
Although Zernike moments had been used on image
retrieval, they seem not robust to image scaling.
According to our experience, the difference of Zernike
moments between the original image and its near-duplicate
is sensitive to image content. Unfortunately, image scaling
is a very common process to generate near-duplicate
videos. To reduce the impact of not only geometric
scaling but also image content on near-duplicate videos.

To reduce the impact of image content on near-duplicate video retrieval, a reference-based approach is adopted. This means that we calculate and consider the
difference of Zernike moments between the original
frame and its quarter version as a reference value.

For the feature \( f_m^Q \) of each key-frame in the query
video \( v^Q \), its reference value can be computed. To search near-duplicate frames, the feature vector
\[ f_1^T, f_2^T, ..., f_n^T \] of one key-frame of the test video
\( v_i^T \) can have the corresponding difference of Zernike
moments with respect to \( f_m^Q \) in \( v^Q \). If the difference
between \( f_m^Q \) and \( f_m^Q \) is lower than the reference value
of \( f_m^Q \), the video frame is considered as a near-
duplicate. Then a binary sequence \([S_1^Q, S_2^Q, ..., S_n^Q]\] can be obtained.

3.3 Temporal analysis

In addition to spatial analysis for each key-frame, we also
consider the results of similarity measurement from
all of key-frames to increase the performance of the
proposed method. Here we consider each key-frame as a
sensor and whether one key-frame is a near-duplicate as
the output of the sensor. It is expected that determining
whether a key-frame is a near-duplicate is a binary hy-
pothesis testing problem. Then the final decision can be
obtained by combining all of output of sensors based on
multiple-sensor fusion concept [13].

We define the state of two hypothesis \( H_0 \) and \( H_1 \) for
each sensor, where \( H_0 \) represents that \( v_i^T \) is not the
NDV of \( v^Q \) and \( H_1 \) means \( v_i^T \) is the NDV of \( v^Q \).
Since determining whether a key-frame is a near-duplicate is a
binary hypothesis testing problem, we examine all of
key-frames and then a binary sequence \([S_1^Q, S_2^Q, ..., S_n^Q]\]
can be obtained below:
\[
S^Q = \begin{cases} -1 & \text{if } H_0 \text{ is declared} \\ +1 & \text{if } H_1 \text{ is declared} \end{cases}
\]
(9)

Based on the Bayesian criterion, the fused decision \( D \)
can be expressed as follows:
\[
D = \text{sgn}\left([-Q + \sum_{m} (\omega^m \cdot S^Q)]\right)
\]
(10)
where \( Q \) is a control factor. The weight \( \omega^m \) is expressed
as follows:
\[
\omega^m = \delta(S^Q - 1) \cdot \log \frac{1 - P_{ FP}}{P_{ FN}} + \delta(S^Q + 1) \cdot \log \frac{1 - P_{ FP}}{P_{ FN}}
\]
(11)
where \( \text{sgn}(\cdot) \) denotes a sign function (\( \text{sgn}(x) = 1 \) for \( x > 0 \)
and \( \text{sgn}(x) = -1 \) for \( x < 0 \)); \( \delta(x) \) is the impulse
function (\( \delta(x) = 1 \) for \( x = 0 \) and \( \delta(x) = 0 \) for \( x \neq 0 \)). \( P_{ FP} \)
is the number negative case labeled as positive; \( P_{ FN} \)
refer to the number of the positive case which is incor-
rectly labeled as negative. Finally we can decide if the $v_i^T$ is the NDV of $v_i^O$ by $D$:

$$\begin{cases} D < 0 & \text{if } H_i \text{ is declared} \\ D \geq 0 & \text{if } H_i \text{ is declared} \end{cases} \quad (12)$$

Both $P_{FP}$ and $P_{FN}$ can be estimated from the training data. The control factor $Q$ can be used to adjust the precision of the proposed method.

4. Experimental Results

In this paper, we focus on some common operations, rescaling, mirroring, and logo insertion, for generating NDVs. On the other hand, we utilize three performance measurements, precision, recall, and accuracy rates, to evaluate the proposed method [14]. The performance measurements are expressed below:

$$\text{precision} = \frac{P_{TP}}{P_{TP} + P_{FN}}$$

$$\text{recall} = \frac{P_{TP}}{P_{TP} + P_{FP}}$$

$$\text{accuracy} = \frac{P_{TP} + P_{TN}}{P_{TP} + P_{FN} + P_{FP} + P_{TN}}$$

where $P_{TP}$ and $P_{FN}$ denote the numbers of false and miss detection; $P_{FP}$ refers to the number of the positive cases which is correctly labeled; $P_{TN}$ represents number of negative cases correctly labeled. In the following experiments, we first analyze the ability of Zernike moments to decide the parameter in Eq. (11) and then evaluate the efficacy of the proposed NDVR method.

A. Analysis of Zernike moments

We select 200 pictures from Google website to analyze the ability of Zernike moments. Ten selected images are used to generate near-duplicate versions by using the mirroring, logo insertion and rescaling operations. Since the edge information of each key-frame, we analyze the impact of the threshold in the Sobel filter. As we can see in Table 1, the minimization of $\omega^0$ in Table 1 occurs when threshold = 2; when the threshold = 1, we can get the minimum of $P_{FN}$. To consider simultaneously $P_{FP}$ and $P_{FN}$, we set the threshold value as 1.To prevent the zero problem of log function, we set $P_{FN}$ a small value and rewrite Eq. (11) as follows:

$$\omega^0 = \delta(S^0 - 1) \cdot 9.1415 + \delta(S^0 + 1) \cdot 2.7104 \quad (13)$$

B. Performance of NDVR

After the parameters are measured, 200 test videos are download form TRECVID website [15] for NDVR test.

Table 1 $P_{FP}$ and $P_{FN}$ while different thresholds in the Sobel filter

<table>
<thead>
<tr>
<th>Threshold</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_{FP}$</td>
<td>6.65%</td>
<td>5.1%</td>
<td>3.3%</td>
<td>12.1%</td>
<td>20.8%</td>
<td>24.2%</td>
</tr>
</tbody>
</table>

Ten video clips are selected to produce near-duplicated videos by using three operations, mirroring, logo insertion, and rescaling. We analyze the correlation between $Q$ and the efficiency of the proposed method and Fig. 4 illustrate the result.

As we can see in Fig. 4, there is a cross point of precision and recall curve at $Q = 5$. For the further analysis, the accuracy with each value of $Q$ are also calculated and shown in Table 2. The highest value of accuracy rates can be obtained when $Q = 8$. Due to the consideration between precision & recall and accuracy rates, $Q = 5$ or $Q = 7$ can be selected in the proposed method.

Table 2 Accuracy rates of the proposed method

<table>
<thead>
<tr>
<th>$Q$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>68.9%</td>
<td>78.7%</td>
<td>85.8%</td>
<td>91.3%</td>
<td>93.5%</td>
</tr>
</tbody>
</table>

5. Conclusions

In this paper, we present a NDVR method developed based on Zernike moments. After shot change detection, Zernike moments are computed from each key-frame of videos as invariant features. We measure the key-frame similarity by computing the difference of Zernike moments between key-frames of the query and test videos. To achieve near-duplicate video retrieval, each key-frame is considered as an individual sensor and then evaluating all of key-frames is considered as multiple sensors. The results of examining key-frames are fused to obtain a better performance of near-duplicate video retrieval. To evaluate the proposed method, we collect a lot of near-duplicate videos. The accuracy rate of the proposed method can be up to 98%. Experimental results show that the proposed method can achieve near-duplicate video retrieval.

In the future, by re-design the equation of proposed similarity measure, we could do the NDV which not only find the duplicate video in database but also discover the duplicate clip in video. Furthermore, we may combine the proposed method with SURF feature matching technology to increase the accuracy rate and analyze the possible operations for generating near-duplicate videos.
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References