Identification and Elimination of Similar Images in an Event Image Set

Hanumanthappa. M, Ph.D
Associate Professor
Department of Computer Science and Applications
Bangalore University, Bangalore

S. Regina Lourdhu Suganthi
Research Scholar
Department of Computer Science and Applications
Bangalore University, Bangalore

ABSTRACT :

Over the past decade Video and Image data is accumulated in the storage media of various commercial organizations, government and educational Institutions. Events are organized round the year in these organizations and are recorded through the digital devices installed at the event venues. Eventually the data is piled up in the electronic vaults and the end-users are unaware of the implications and importance of this data. Thus an automated system is needed for the image data to be indexed, captioned and maintained as an archive to extend quick summary of events for preparing annual documents, magazines and departmental newsletters. This paper focus on preprocessing of the captured image data to identify and eliminate similar images. The resulting image set thus eliminate redundant data and in turn reduce the storage space.

Keywords :

CBIR, RBIR, FEBIC, Structural SIMilarity (SSIM), Human Visual System (HVS)

1. INTRODUCTION

Image and video data piled up in servers located at event venues pose a tremendous challenge in terms of storage and retrieval. The video and image data captured during the events are for a specific duration namely a few hours or a few days. Multiple shots of the same scenes are captured successively with similar image content resulting in redundant data. These redundant data occupy considerable storage space. Identifying redundant images can be fastened by considering the consecutive images and comparing them using various similarity measures. This paper focuses on identifying such similar images by extracting image features.

The paper is organized as follows :

Section 2 presents the literature survey of the related topics. Section 3 presents the proposed framework. Section 4 gives the detailed process flow of the framework. Section 5 presents the experimental results of an event data set and Section 6 concludes with scope of the work.

2. LITERATURE REVIEW

Content Based Image Retrieval (CBIR)[3] is a technique for retrieving an image from an image database based on a query image. It maps the features of an image with its semantics. Generally texture, color and shape features are used to describe the image content[2][7]. Another technique known as Region Based Image Retrieval (RBIR) improves the performance of retrieval by extracting the features of an image after segmenting the image into regions. Segmentation[9][10][5] is a very challenging area pertaining to human perception. It has been shown in many applications that the local features such as texture, energy play a significant role in identifying the similarity between images[6].

Various feature elements in an image signify different properties[11]. Based on the applications, the necessary features can be extracted from an image[4]. There are various ways of obtaining feature elements based on properties of an image that would enable Feature Element Based Image Classification (FEBIC). These include color histograms, Wavelet co-efficients[1], Color properties can be obtained by dividing images into several clusters with a perpetual grouping on hue histogram. The color cardinality for each cluster can be taken as the central hue value, color-coherence vector, color-auto-correlogram can also be calculated[8].

Structural similarity measure (SSIM) is a quantitative measure to automatically predict the image quality with reference to HVS[12]. SSIM compares local patterns of pixel intensities that have been normalized for luminance and contrast. It is used to measure perceived changes in structural information variation. If X and Y represent the intensities of two images, the system separates the task of similarity measurement into three comparisons: luminance, contrast and structure. The luminance is estimated as the weighted mean intensity with a circular-symmetric Gaussian weighting function w = { wi | i= 1,2, …, N}, with the standard deviation of 1.5, normalized to unit sum.

$$\mu_x = \sum_{i=1}^{N} x_i w_i$$

where X_i's are the intensities of the image.

The luminance comparison function is then a function of μ_x and μ_y. The standard deviation σ_x is used as an estimate of the signal contrast :

$$\sigma_x = \left(\frac{1}{(N-1)} \sum_{i=1}^{N} w_i (x_i - \mu_x)^2 \right)^{½}$$

The contrast comparison is then a comparison of σ_x and σ_y. The signal is divided by its own standard deviation, so that the two signals being compared have unit standard deviation. The structure comparison is conducted on these normalized signals $(X - \mu_x) / \sigma_x$ and $(Y - \mu_y) / \sigma_y$. Finally, the three components are combined to yield an overall similarity measure.

3. FRAMEWORK

Step 1 : Divide the Image data into groups based on timestamp
Step 2 : Reduce the image size, Segment the image and Extract image features
Step 3 : Calculate SSIM for successive images within a Group
Step 4 : Eliminate one of the two similar images within each pair
Step 5 : Compute exhaustive similarity measures within a group and eliminate one of the two similar images
Step 6 : Compute SSIM for the last image in group i and first image of group i+1, if similar, eliminate one of them. This will result in distinct image data set.

4.PROCESS FLOW OF THE FRAMEWORK

4.1 Image grouping using Timestamp

This approach is a divide-and-conquer technique to minimize the computation time.

Events are generally organized for a duration of few hours or for few days. The image**s** acquired during these events can be grouped based on the timestamp. For instance, if an event took place for a duration of m days, then the image set can be divided into m groups. These groups can further be divided into sub groups taking into account the time duration of the days' events. Thus, Group 1 referring to day 1 events can further be divided based on one session duration, thus giving rise to n sub groups namely Group 1.1 to Group 1.n as shown in (Figure 1).

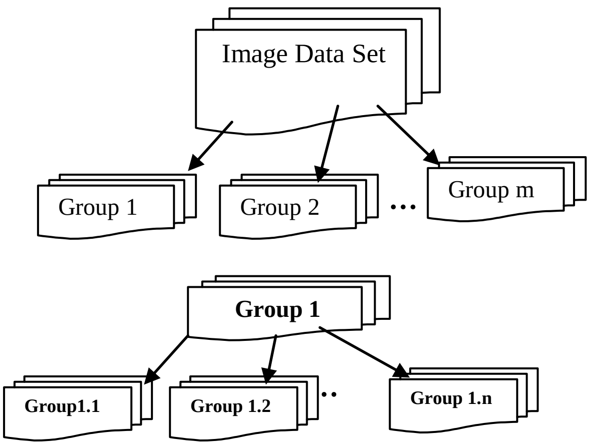

Figure 1 : Image Grouping Using Timestamp

4.2 Size Reduction, Segmentation and Extraction of Image features

The images captured are generally used for preparing documents and printing news letters and hence the first step to save the storage space is to resize the image as per the need.

Neither the color features such as R-Red, G-Green, B-Blue in the RGB color space Nor the values of H-Hue, S-saturation, V-Value components in the HSV color space (after converting to the HSV color space) yield much to predicting the similarity between two images. Hence other features such as luminance, contrast and structure measures are extracted. The global SSIM measure for the complete image is computed and shown in table 4. The value obtained too do not predict the similarity. Thus if an image is segmented into m by n totaling m*n segments and the features viz., luminance, contrast and structure are extracted for each of the m*n segments then the SSIM index computed for these segments results in appealing values due to the fact that the mean and variance computed are local to the segments.

4.3 Calculation of SSIM for successive images within a Group

Analyzing the fact that the images taken during a single session duplicate the image content, the redundant images can be identified easily by successive comparison. If there are s images in a group, image(1) and image(2), image(2) and image(3), … ,image(s-1) and image(**s**) are compared using similarity measure.

Image i and Image i+1 are first divided into m*n segments, the SSIM measure is computed for each of the corresponding segments of Image i and Image i+1. An image group with s images will result in a matrix of order m*n by s-1 SSIM values. If most of the SSIM values of the segments are above 0.60 for an image pair (i, i+1) then, Image i and Image i+1 are identified as similar.

4.4 Elimination of similar images

One of the two similar images is retained and the other is eliminated. It is justifiable to eliminate the second image in the image pair (i ,i+1). Assuming that the image pairs (i, i+1), (i+1, i+2) and (i+2, i+3) result in favour of similarity, then the resultant set will consist only of Image i after elimination.

	Image Pairs				
	13 & 14	**14 & 15**	**15 & 16**	**16 & 17**	**17 & 18**
1	**0.3308**	**0.4944**	**0.5416**	**0.8107**	**0.2028**
2	**0.5593**	**0.4514**	**0.5262**	**0.7931**	**0.1718**
3	**0.2556**	**0.7141**	**0.7410**	**0.6059**	**0.1882**
4	**1.5420**	**1.6650**	**0.4012**	**0.6790**	**0.3628**
5	**0.8069**	**0.4229**	**0.4720**	**0.7003**	**0.5321**
6	**0.4216**	**0.6822**	**0.5798**	**0.3749**	**0.3475**
7	**0.4934**	**0.4208**	**0.4787**	**0.8650**	**0.6698**
8	**0.4934**	**0.4481**	**0.5107**	**0.7684**	**0.5848**
9	**0.3975**	**0.5333**	**0.4734**	**0.5214**	**0.5415**

4.5 Exhaustive computation

Elimination of similar images from the group will considerably reduce the group size. Now an exhaustive computation of SSIM measure can be done by calculating SSIM values for the image pairs (1,2), (1,3),(1,4),…(1,s1) where s1 is the size of the group. This process is repeated till the image pair (s1-1,s1) and for all the image groups.

4.6 Inter group Comparison

The images within each group after exhaustive computation of SSIM index will consist of distinct images. Hence the last image of group i must be compared with the first image of group i+1 for all i. Since the image set consists of images of different sessions, we assume that the images in two groups will not be similar and hence the above mentioned procedure is sufficient in identifying similar images in two groups.

5. EXPERIMENTAL RESULTS

Test Data Set : Two-day Seminar images held at an Institution.
Total Images : 702
Number of Groups : 16
Group Size : { 18, 41, 21, 74, 16, 17, 21, 51, 35, 50, 56, 107, 18, 47, 44, 86}
No. of segments for each Image is 9.
SSIM Values for Group1 is a matrix of size (9, 17) and are shown in the tables 1, 2 & 3

Table 1

Segments	Image Pairs					
	1 & 2	**2 & 3**	**3 & 4**	**4 & 5**	**5 & 6**	**6 & 7**
1	**0.7430**	**0.2852**	**0.6934**	**0.2869**	**0.3282**	**0.5054**
2	**0.9520**	**0.5396**	**-0.1598**	**0.4797**	**0.3225**	**4.8419**
3	**0.9801**	**0.1494**	**0.2857**	**0.3118**	**0.5305**	**0.2841**
4	**0.7313**	**0.5353**	**0.2681**	**0.3654**	**1.9888**	**0.4703**
5	**0.8856**	**0.9939**	**0.3768**	**0.5563**	**0.3461**	**0.8089**
6	**0.9222**	**0.2666**	**0.0625**	**0.5769**	**0.5862**	**0.3547**
7	**0.2399**	**0.0860**	**0.1733**	**0.3246**	**0.6782**	**0.3894**
8	**0.3813**	**0.0765**	**0.0234**	**0.7627**	**0.3581**	**0.4204**
9	**0.2710**	**0.0655**	**0.1681**	**0.5239**	**0.4378**	**0.4987**

Table 2

Segments	Image Pairs					
	7 & 8	**8 & 9**	**9 & 10**	**10 & 11**	**11 & 12**	**12 &13**
1	**0.3885**	**0.2971**	**0.7462**	**0.7104**	**0.3603**	**0.4302**
2	**0.2870**	**0.2851**	**0.1925**	**0.8414**	**0.3994**	**0.4686**
3	**0.1667**	**0.1050**	**0.1931**	**0.6176**	**0.4515**	**0.2763**
4	**0.3793**	**0.4701**	**0.6866**	**0.5587**	**0.4887**	**1.6380**
5	**0.7184**	**0.8780**	**1.0229**	**1.1224**	**0.8829**	**0.5006**
6	**0.3419**	**0.5948**	**0.3450**	**0.5430**	**0.3728**	**0.4851**
7	**0.2055**	**0.3549**	**0.3004**	**0.3992**	**0.4544**	**0.5110**
8	**0.4379**	**0.5627**	**0.5037**	**0.5755**	**0.4009**	**0.4202**
9	**0.3822**	**0.3925**	**0.3831**	**0.7371**	**0.5608**	**0.5001**

Table 3 Segments

It is clear from the results that image pairs (1,2), (10,11), (16,17) are similar.

Figure 2 : Image Pair (1,2)

Figure 3 : Image Pair (10,11)

Figure 4 : Image Pair (16,17)

Group 2 resulted in 14 image pairs that are similar. Similar image ratio in group 1 = 3/18 =0.1667and in group 2 = 14/41 = 0.3415.

The global SSIM values for group 1 image set is shown in the table 4.

Table 4 : SSIM values without segmenting the images

Image Pairs	SSIM Index
1 & 2	**0.6109**
2 & 3	**0.1948**
3 & 4	**0.2153**
4 & 5	**0.2514**
5 & 6	**0.2388**
6 & 7	**0.2103**
7 & 8	**0.2003**
8 & 9	**0.1750**
9 & 10	**0.2306**
10 & 11	**0.4414**
11 & 12	**0.2759**
12 & 13	**0.2414**
13 & 14	**0.2106**
14 & 15	**0.2355**
15 & 16	**0.1520**
16 & 17	**0.2883**
17 & 18	**0.2288**

It is evident that local features play a significant role in measuring similarity for this application. Thus the storage space required for the resulting distinct data set after size reduction, identification and elimination of similar images is less.

6. CONCLUSION

The feature elements extracted from the image convey different characteristics. Identification of the suitable feature is largely application specific. For identifying similar images in a large image set taken during various events, we have used a measure that combines luminance, contrast and structure along with segmentation. This yields a promising measure for identifying similar images. The results can be improved by combining some more image features.

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