AN IMAGE RETRIEVAL ALGORITHM USING MULTIPLE QUERY IMAGES

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ABSTRACT

In this paper, an image retrieval algorithm using multiple query images is proposed. The algorithm is based on multi-histogram intersection techniques. For each query image, a color histogram and a texture histogram are extracted. Then multi-histogram intersection is used to measure the similarity between the query images and each image in the database. The ranking in similarity is used to determine the images to be retrieved. This approach can be applied to image retrieval with relevance feedback and to component based image retrieval. Results are provided showing the improvement in precision that is afforded by the multi-example retrieval paradigm.

1 INTRODUCTION

Content based image retrieval (CBIR) has been an active research direction in the past years. It has many advantages over traditional image retrieval based on text annotation. For example, in a digital library, CBIR allows users to find images that have not been catalogued or have been partially catalogued. Of course, CBIR will not replace text based searches entirely – where text annotation exists, but CBIR will augment the searching capability for multimedia libraries. Because of the attractive features of automated cataloguing and retrieval as well as an explosion in the libraries containing digital imagery, CBIR has widely been applied to different fields, such as education [1], medicine [2], industry [3], and so on.

More than a few image retrieval algorithms have been proposed. For the purpose of this paper, the CBIR methods can be divided into two categories: single-example based image retrieval [4][5][6] and multi-example based image retrieval [7][8][9][10]. Multi-example image retrieval has been proven to be effective in providing feedback [7] for enhancing the single-example image retrieval results. In these applications, image retrieval is carried out using a single image example, and then the relevance of the output retrieved images is scored by users for training a classification model, such as a neural network[9], a Bayesian model [10], and so on, to modify the similarity measure to match users' expectation. Thereafter, the model is used to perform the retrieval.

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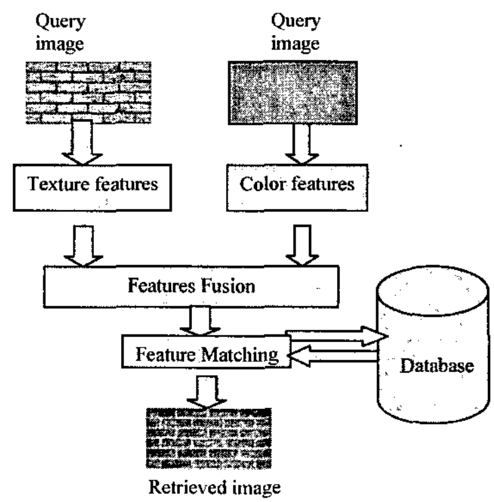


Figure 1. Component based image retrieval using multiple query images

The innovation introduced in this paper is multi-component image retrieval in which the components are features from multiple images. Assuming that we have two query images, one image may contain a texture of interest and the other image may contain colors of interest. We can use the texture features of the first image and the color information of the second image to retrieve image with similar texture to that of the first image and similar color information similar to that of the second image. The general framework of component based image retrieval is illustrated in Figure 1. Obviously, in this type of application, there are not enough examples to form a training set, so some complex models, such as neural networks, Bayesian models are not practicable. This paper describes an image retrieval algorithm using multiple query images. The algorithm can be applied to component based or full image based multi-queries.

2 IMAGE FEATURE REPRESENTATION

2.1 Color feature representation

For each image, a quantized histogram is recorded. Although perceptually motivated color spaces exist, such as l*a*b*, we utilize the RGB color space to achieve enhanced processing and image format [1].

2.2 Texture feature representation

Many techniques have been proposed to measure texture similarity. Gray level co-occurrence matrices were proposed in [11] and Gabor filter decomposition was introduced in [12]. Alternative methods of texture analysis for retrieval include the use of wavelets [13] and fractals [14]. Indeed, our texture description method is based on wavelets. Wavelet based texture retrieval is founded on the assumption that the energy distribution in the frequency domain can be used to capture texture. Let an image be decomposed into K subbands. Then the energy in the i-th subband can be computed as

$$E_i = \sqrt{\frac{\sum_{j=1}^{K_i} x_{i,j}^2}{K_i}} \tag{1}$$

where $x_{i,1}, x_{i,2}, \ldots, x_{i,K_i}$ are the wavelet coefficients in the i-th subband and K_i is the number of the wavelet coefficients in the i-th subband. Using the energy in K subbands, we can obtain a feature vector representing the texture characteristics of the image

$$E = (E_0, E_1, \ldots, E_{K-1}). \tag{2}$$

In this paper, the multiscale decomposition technique developed in [15] is used to decompose the images into different subbands. In this technique, first the original image is decomposed into four subbands: the low–low subband, the low-high subband, the high-low subband and the high-high subband; then, the low–low subband is further decomposed into four other subbands similar to the subbands obtained by the original image. This decomposition can be carried out further as necessary. In this paper, we employ three levels of decomposition.

3 IMAGE RETRIEVAL USING MULTIPLE QUERY IMAGES

In multiple query image retrieval, because each image has several types of features, such as texture and color, the question arises as to how to employ features from multiple images simultaneously. We facilitate two ways in which to use the features. One approach is to use the same feature from different query images to achieve retrieval, and the second way is to combine different features from different query images.

3.1 Color feature based image retrieval using multiple histograms intersection

In this subsection, we will consider how to use the color features from different query images to enact retrieval. Multiple histogram intersection is used to achieve the aim. A multiple histograms intersection is a processing which is similar to the histograms intersection using two images. Let I_Q^i (i=1,..,N) denote the i-th query image, I_D be an image in the database. Multiple histogram intersection is defined as

$$D_H(I_Q^1,\ldots,I_Q^N,I_D) = \frac{\sum_{j=0}^{n-1} \min(H(I_Q^1,j), H(I_Q^2,j),\ldots,H(I_Q^N,j), H(I_D,j))}{\sum_{j=0}^{n-1} H(I_D,j)} \tag{3}$$

where $H(I_Q^i, j)$ is the j-th bin of the histogram of image I_Q^i and $H(I_D, j)$ is the j-th bin of the histogram of image I_D, and n is the number of bins in the histogram.

Equation (3) can be modified to include some weights as follows:

$$D_H(I_Q^1,\ldots,I_Q^N,I_D) = \frac{\sum_{j=0}^{n-1} \min(y^1 H(I_Q^1,j), y^2 H(I_Q^2,j),\ldots,y^N H(I_Q^N,j), H(I_D,j))}{\sum_{j=0}^{n-1} H(I_D,j)} \tag{4}$$

where $y^k (k = 1,2,\ldots,N)$ determine the relative weighting for color features from different query images. Here we will allow only binary weights of {0, 1}. A weight of zero would exclude color feature from particular query image. When all weights equal to 1, the color features from all the query images is used for searching.

3.2 Texture feature based image retrieval

A texture histogram intersection is developed to measure the similarity of texture when multiple query images are employed. The idea is similar to color histogram intersection. The only difference is that we use the energies from different subbands to replace the frequency of each color bin in color histogram intersection. Let $E_Q^i = (E_0^i, E_1^i, \ldots, E_{K-1}^i)$ be the subband energies of query image i, and $E_D = (E_0^D, E_1^D, \ldots, E_{K-1}^D)$ be the subband energies of an image in database.

The texture similarity measure measured between query images and the image in database is defined as

$$D_T(I_Q^1,\ldots,I_Q^N,I_D) = \frac{\sum_{j=0}^{K-1} \min(x^1 E_j^1,\ldots,x^N E_j^N, E_j^D)}{\sum_{j=0}^{K-1} E_j^D} \tag{5}$$

where x^k is the weight for the k-th query image. For texture, we also allow only the bi-valued weights of {0, 1}. A weight of zero would exclude texture feature from particular query image. When all weights equal to 1, the texture features from all the query images will be used for searching.

3.3 Combining Texture feature and color feature for image retrieval

Now let us consider how to use the color and texture features from different query images to perform retrieval. Combining different features is a unique challenge for multi-example image retrieval. To combine two different features from different images in image retrieval, a matching functional combining the two features is required. The matching functional determines the "goodness" of match between the query images specified by users and an image in the database.

Given multiple query images I_Q^i (i=1,..,N), and an image in the database I_D, the matching functional is computed using

$$D(I_Q^1,...,I_Q^N,I_D)=w_1D_H(I_Q^1,...,I_Q^N,I_D)+w_2D_T(I_Q^1,...,I_Q^N,I_D) \quad (6)$$

where $D_H(I_Q^1,...,I_Q^N,I_D)$ is the similarity between normalized color histograms similarity and $D_T(I_Q^1,...,I_Q^N,I_D)$ represents the normalized similarity of texture. The parameters w_1, w_2 determine the relative weighting for the image features. Given a set of images with known results *a priori*, we can determine the weights using a cross-validation technique.

4 EXPERIMENTAL RESULTS

To evaluate the performance of our multi-example image retrieval algorithm, we implemented a prototype image retrieval system. The system supports both of the single example image retrieval and multi-example image retrieval. The experimental database is the "Washington" image database with about 800 images [16]. The performance of the algorithm is measured by precision, which is defined as

$$precision = \frac{Number\ \ of\ \ relevant\ \ images\ \ retrieved}{Number\ \ of\ \ total\ \ images\ \ retrieved} \quad (7)$$

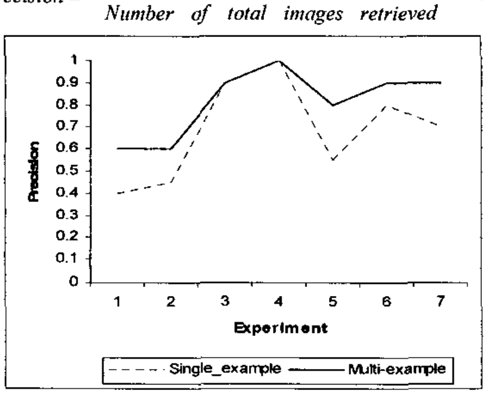
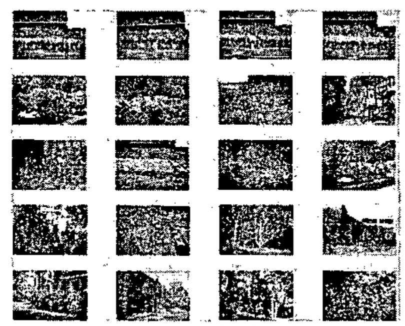


Figure 2. Precision comparison using different image retrieval algorithms

First we tested the performance of single example image retrieval and multi-example retrieval algorithm for relevance feedback. For each retrieval algorithm, we performed seven different image retrieval experiments. For each experiment, we first selected one image as a query image randomly and then obtained the retrieved images. Then the users were asked to select the images from the retrieved images which are related to the expected image. These selected images were used as query images for next step. In the next step, the algorithm developed in this paper was used to perform retrieval again via (6). The results in terms of precision are shown in Figure 2. The dotted line represents the retrieval results using single example image retrieval algorithm. The solid line represents the retrieval results using multi-example image retrieval algorithm which the query images are the images selected from the retrieved images by single example. Figure 2 indicates that the feedback processing has improved the retrieval results. Figure 3 shows the retrieval examples respectively by single example and multi-example retrieval algorithm in the above processing.



(a) Image retrieval using single query

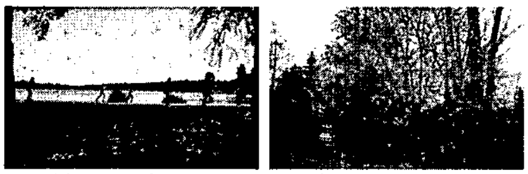
(b) Image retrieval using multiple queries

Figure 3. Image retrieval using single query image and multiple query images.

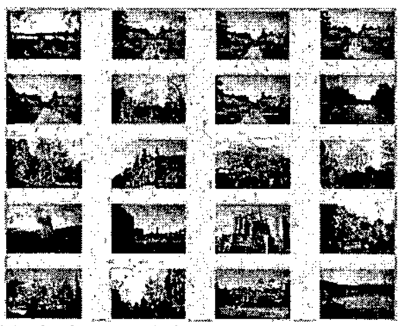
Second we compared the performance of the single example image retrieval and multi-example retrieval algorithm for component based image retrieval. Here we attempted to retrieve the images with similar color information to the image in Figure 4(a) and similar texture information to image in Figure 4(b). Figure 4 (c) and (d) show the retrieved results respectively by single example and multi-example retrieval algorithm. From this preliminary result, we can see that the multi-example retrieval algorithm effectively exploits a trade-off between color and texture.

5 CONCLUSION

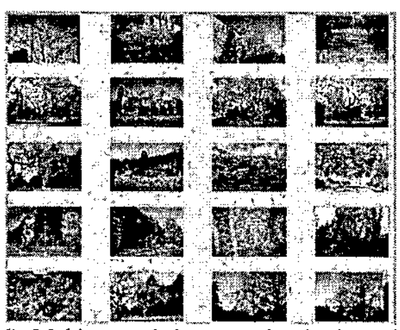
A new image retrieval algorithm using multi-histogram intersection is proposed for multiple examples based image retrieval. Our algorithm can be applied to feedback processing after single example image retrieval for improving the retrieval results and component based image retrieval. Early experimental results have shown the promise of this effective approach. Further research should be directed toward the following topics: (1) Combining multiple regions in different images (using segmented imagery); (2) fusing shape information; (3) validating methods by more extensive testing.



(a) Query image 1 (b) Query image 2



(c) Single example image retrieval using color



(d) Multi-example image retrieval using color and texture information from two different image

Figure 4. Components based image retrieval

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