Content-Based Image Retrieval Using Optimal Feature Combination and Relevance Feedback

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***Abstract*—With the rapid development of the multimedia technology and Internet, content-based image retrieval (CBIR) has become an active research field at present. Many researches have been done on visual features and their combinations for CBIR, but few on the performance comparison of different visual feature combinations. Therefore, in the paper, different visual feature combinations are firstly compared in retrieval experiments. Moreover, only using low-level features for CBIR cannot achieve a satisfactory measurement performance, since the user's high-level semantics cannot be easily expressed by low-level features. In order to narrow the gap between user query concept and low-level features in CBIR, a multi-round relevance feedback (RF) strategy based on both support vector machine (SVM) and feature similarity is adopted to meet the user's requirement. The experiment results showed that this SVM and feature similarity based relevance feedback using best feature combination can greatly improve the retrieval precision with the number of feedback increasing.**

Keywords-content-based image retrieval; visual features combination; support vector machine; relevance feedback

I. INTRODUCTION

With the development of the multimedia technology and Internet, the image data is rapidly increasing. Facing increasing number of image resources, it is an important issue that the users who have the specific requirements can quickly and efficiently select the images from the database. In order to meet the user-required images quick searching from such a huge image database, content-based image retrieval (CBIR) has become one of the most popular and challenging problems in visual information retrieval [1]. By extracting information clues from the media content, CBIR uses similarity matching technology and combines relevance feedback to reduce searching time for retrieval in large image databases.

Since an image usually embodies rich information, mostly, one feature of image such as color, texture, shape, spatial relationship can only represents part of the image properties and the one-sided image contents. Therefore, the combination of these features is generally being used for the computation of multi-dimensional feature vector [2, 3]. However, few researches were done on the performance comparison of different combinations of these features. Moreover, only using low-level features for CBIR cannot achieve a satisfactory measurement performance, since the user's high-level semantics cannot be easily expressed by low-level features. To narrow the gap between low-level features representation of images and the user's high-level semantic concepts, Support Vector Machine (SVM) based relevance feedback (RF) is employed to learn user's query concepts [2, 4, 5, 6]. SVM is effective for small sample dataset learning, and shows good performance in pattern recognition. However, there still exist some problems in the sorting results when SVM is applied to CBIR, for example, those ranked in the front are sometimes irrelevant images, while the relevant images are ranked behind [7]. To avoid the problem, a multi-round feedback strategy based on both SVM and feature similarity is adopted to boost the retrieval precision.

The rest of the paper is organized as follows. In Section II, visual features extraction is described, including color and texture, which are commonly used in visual features expression. The image retrieval method used in the experiment is described in Section III. Section IV gives detailed experiment and performance comparison and discusses the experimental results. Section V gives some concluding remarks and discusses the future work.

II. VISUAL FEATURES SELECTION AND COMBINATION

Visual features extraction plays an important role in image expression in CBIR. There are various kinds of low-level visual features to represent an image, such as color, texture, shape, and spatial relationship. Since one type of features can only represent part of the image properties, many researches have been done on the combination of these features. Color and texture features were tried to be combined for CBIR in [8]. Color, texture and shape features were proposed to be combined to make an intelligent solution for efficient searching of images in [9]. One color feature and three texture features were applied to express image information in [2], and a novel framework for combining color, texture and shape information was presented in [3]. Presently, few researches were reported on the comparison of the retrieval performance using different combinations of features. In the paper, for comparison, three kinds combinations of color and texture information are used as input feature vectors for CBIR to represent image features. TABLE I gives the details of each feature vector.

TABLE I. THE COMPONENTS OF VISUAL FEATURE VECTORS

Visual Features		Feature Vectors	
		Feature Extraction Method	***Vector Components***
Color feature		Color moment	Color mean and color variance of R, G, B
Texture features	Wavelet transform feature	Wavelet transform	Entropy and energy of 10 sub-images obtained by 3 levels of Daubechies-2 wavelet decompositions
	Co-occurrence matrix feature	Co-occurrence matrix	Contrast, energy and correlation of co-occurrence matrixes for 4 directions
	Gabor feature	Gabor filters	Mean and standard deviation of the coefficients on 3 scales and 4 directions

TABLE II. VISUAL FEATURE COMBINATIONS

Combination ID	Ways to Combine Visual Features		
	Color Feature	***Texture Feature***	
		Texture Feature 1	***Texture Feature 2***
Combination 1	RGB color moment	Wavelet transform	Co-occurrence matrix
Combination 2	RGB color moment	Co-occurrence matrix	Gabor
Combination 3	RGB color moment	Gabor	Wavelet transform

A. Color

The color feature is one of the most commonly used features in image retrieval because of its simplicity and rotational invariance. The well-known color space is RGB in which every color is made up of three fundamental color components red, green, and blue. The color feature engaged in the experiment is color moment which has been applied in [10]. For the employed color moment, two moments, that is, color mean and color variance [10], are calculated in the RGB space respectively to generate a 3×2 dimensional color feature vector (TABLE I).

B. Texture

The texture feature is another type of important and useful visual information for image retrieval. Many real world images include textures. In the paper, three types of texture feature extraction techniques wavelet transform, co-occurrence matrix, and Gabor filters are applied to express texture features for images.

1) Wavelet transform feature: The wavelet transform-based texture technique is a popular domain in texture feature extraction, and it has been successfully used in image retrieval [11]. In this study, the 2D Discrete Wavelet Transformation (DWT) is employed to extract texture features. Firstly, the original color images are transformed to gray images. Then three levels of Daubechies-2 wavelet decompositions are performed on these gray images. Each level of decomposition results in four sub-images, including the approximation, horizontal, diagonal, and vertical information of each image respectively. As a result, ten sub-images are obtained in different scales and orientations. Each of these ten sub-images is applied to compute the entropy and energy separately which are used as the 10×2 dimensional texture features (TABLE I).

2) Co-occurrence matrix feature: The co-occurrence matrix is a two dimensional histogram to compute statistical texture features [12]. It uses a square matrix to calculate how often a pixel with a gray-level value occurs in specific spatial relationships to an adjacent pixel with another value. Exactly speaking, the $(i, j)th$ element of the co-occurrence matrix represents the probability that gray level i co-occurs with gray level j at a specified step length and direction. According to different step lengths and directions, different co-occurrence matrixes can be obtained correspondingly. In the paper, co-occurrence matrixes are gotten for four orientations ($0, \pi/4, \pi/2, 3\pi/4$) with step length being 5 [13]. Then three features contrast, energy, and correlation are extracted from these co-occurrence matrixes separately to form a 4×3 dimensional texture features (TABLE I).

3) Gabor feature: Gabor functions are being used as another texture feature extraction technique for image retrieval [14], since they can capture texture properties at different scales and orientations to a large extent. The Gabor filters take a Gabor transform to the image with different scales and orientations. Based on the mean and the standard deviation of the coefficients on each scale and orientation, a feature vector is formed to represent the texture information of images. In the paper, a bank of Gabor filters with four orientations ($0, \pi/4, \pi/2, 3\pi/4$) and top three spatial frequencies in the image [15] are used to extract texture features and a $4\times3\times2$ dimensional texture features is generated (TABLE I).

C. Visual Feature Combination

Since one type of image features can only represent part of the image properties, the combination of visual features can perfect the image information expression. However, various combinations of visual features may result in very different retrieval results. Therefore, to make a comparison of the different combinations, color and texture features are selected in the experiment. The combination is divided into two levels. One is the combination of color and texture features and the other is the combination of two textures extracted by two different texture feature extraction techniques. To the latter combination, as three texture features are introduced in the paper, there will be, therefore, three kinds of texture feature combinations. Each kind of texture feature combination is to be combined with the color feature so as to form the former level combination of visual features, that is, the combination of color and texture features.

TABLE II gives the details on the ways of combining visual features.

III. IMAGE RETRIEVAL METHOD

The process of image retrieval is described as follows. Firstly, the query image is provided by the user and the query image is changed into the representation of feature vectors. Then according to the way of combination of visual features, a combined feature vector is obtained. The similarities or distances between the combined feature vectors of the query image and those of the images in the database are then calculated and only top N images with the minimum distances are returned to the user. If the first retrieval result is not satisfactory, the user can label relevant images as positive and irrelevant images as negative to form training samples. And this relevance feedback information is sent to SVM. By learning this information, the retrieval system returns the more accurate result by the second match, and if necessary, the retrieval system can feed back many times until the user satisfies. Fig. 1 is the process of image retrieval.

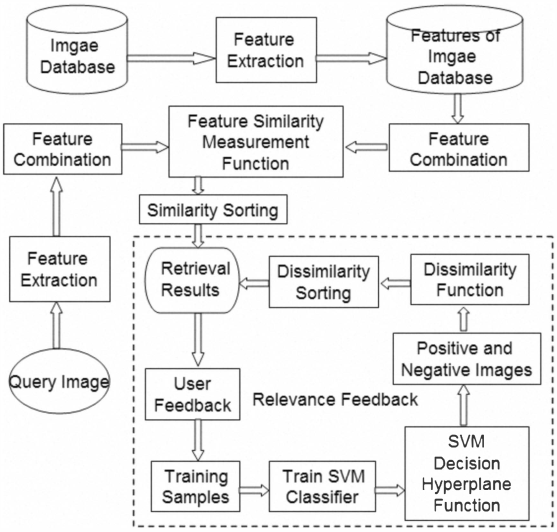

Figure 1. The process of image retrieval.

A. Feature Similarity Measurement

The commonly used similarity measure method is the vector space model, in which they regard the features of an image as a point in the vector space, through calculating the approaching degree of the two points to weigh the similarity of images. In the paper, the Euclidean distance is used to calculate the similarity between the images. For convenience, the feature similarity measurement function is denoted as D^q_{Sim}, which is expressed as follows:

$$D^q_{Sim}(I_i) = w_{color} D^q_{color}(I_i) + w_{textuer\text{-}comb} D^q_{textuer\text{-}comb}(I_i), \quad (1)$$

$$D^q_{color}(I_i) = \left[\left(c_1 - c_1^q\right)^2 + \left(c_2 - c_2^q\right)^2 + \cdots + \left(c_n - c_n^q\right)^2 \right]^{\frac{1}{2}}, \quad (2)$$

$$D^q_{textuercom}(I_i) = \left[\left(t_1 - t_1^q\right)^2 + \left(t_2 - t_2^q\right)^2 + \cdots + \left(t_m - t_m^q\right)^2 \right]^{\frac{1}{2}}. \quad (3)$$

In (1), I_i is an image in the database (i=1,…, M. M is the number of images in the database); $D^q_{color}(I_i)$ and $D^q_{textuer\text{-}comb}(I_i)$ are the similarity measurement functions of color feature and the combination of two texture features by Euclidean distance respectively, and they calculate the distances of image I_i and the query image q in color feature space and texture feature space correspondingly. And w_{color} and $w_{textuer\text{-}comb}$ are the weights of color feature and the combination of texture features in Euclidean distance. In (2), c_j and c^q_j (j=1,…, n) are the components in color feature vectors of image I_i and the query image q respectively with n being the dimension of color feature vector. In (3), t_j and t^q_j (j=1,…, m) are the components in combined texture feature vectors of image I_i and the query image q respectively with m being the dimension of combined texture feature vector.

B. Support Vector Machine

Support vector machine (SVM) is a state-of-the-art machine learning technology, since it has strong theoretical foundations based on Structural Risk Minimization instead of Empirical Risk Minimization [16]. SVM uses kernel to map training samples from original feature space to a high-dimensional feature space. The aim of SVM is to find an optimal separating hyperplane by minimizing an upper bound of the generalization error and meanwhile maximizing the margin between the two support hyperplanes [17]. The basic description of SVM is described as follows.

Given the training samples $T=\{(x_1, y_1),\ldots, (x_l, y_l)\}\in(R^n\times Y)^l$, training data $x_i\in R^n$, their class labels $y_i\in Y = \{1, -1\}$, $i = 1,\ldots,l$, where l is the number of training samples, the separating hyperplane is constructed by solving the following optimization problem

$$\begin{aligned} &\underset{w,b,\xi}{minimize} && \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}\xi_i \\ &subject\ \ to && y_i\left(\left(w\cdot\Phi(x_i)\right)+b\right)\ge 1-\xi_i,\ \ i=1,\cdots,l, \\ & && \xi_i \ge 0,\ \ i=1,\cdots,l. \end{aligned} \quad (4)$$

In (4), Φ (·) is a mapping function to map training data x into a high-dimensional space, where "·" is an inner product. The parameter C is the penalty parameter which is to balance the model complexity and training error, and ξ_i is the slack parameter which allows for some training samples to be within the margin. The optimization of SVM is usually solved in a dual form as follows:

$$\begin{aligned} &\underset{\alpha}{minimize} && \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} y_i y_j K\left(x_i, x_j\right)\alpha_i\alpha_j - \sum_{j=1}^{l}\alpha_j \\ &subject\ \ to && \sum_{i=1}^{l} y_i\alpha_i = 0, \\ & && 0\le\alpha_i\le C,\ \ i=1,\cdots,l. \end{aligned} \quad (5)$$

In (5), $K(x_i, x_j)$ is a kernel representing for $(\Phi(x_i)\cdot\Phi(x_j))$. The kernel function K has various types, such as linear, polynomial, radial basis function (RBF), and sigmoid. By solving (5), $\alpha^* = (\alpha_1^*,\ldots, \alpha_l^*)^T$ can be obtained. Choose a component α_j^* that is within the range (0, C), and, thus, the decision hyperplane can be represented as

$$f(x) = \sum_{i=1}^{l} y_i \alpha_i^* K(x_i, x) + b^*, \qquad b^* = y_j - \sum_{i=1}^{l} y_i \alpha_i^* K(x_i, x_j) \; . \tag{6}$$

C. Support Vector Machine and Feature Similarity Based Relevance Feedback

The basic idea of relevance feedback is that in the process of retrieval, user is allowed to evaluate and label the retrieval results, and point out which are relevant to the query image and which are irrelevant, and then the system uses the user-labeled information as training samples to guide the next round of retrieval so as to make the result closer to user's requirement.

As a machine learning method, SVM has many advantages of solving nonlinear and high-dimensional pattern recognition problems. Therefore, it is widely used in relevance feedback for CBIR. Traditional SVM-based relevance feedback algorithm [5, 6] treats the decision function as an algebraic measure of the distance between a point in the feature space and the hyperplane. Although it can well perform most of the time in relevance feedback, there still exists a problem that in the sorting results, those ranked in the front are sometimes irrelevant images, while the relevant images are ranked behind [7]. To avoid this situation, a SVM and feature similarity based relevance feedback [7] is adopted in the study. The process of relevance feedback based on SVM and feature similarity is described as follows (Fig. 1):

- According to the query image, do the first retrieval based on the similarity of visual features combination. The top N images are returned as the initial retrieval result to the user. Meanwhile, initialize the positive sample set I^+ and the negative sample set I^-.
- Based on the retrieval result, the user selects the relevant images and the irrelevant ones. In the current feedback round, the relevant ones form positive sample set I_1^+, and the irrelevant ones form negative sample set I_1^-. Then I^+ and I^- are updated as follows:

$$I^+ = (I^+ \cup I_1^+) - I_1^-, \qquad I^- = (I^- \cup I_1^-) - I_1^+. \tag{7}$$

- Study the training sample set (x_i, y_i) by using SVM and construct classifier by (6), in which

$$x_i \in I^+ \cup I^-, y_i = \begin{cases} +1, & x_i \in I^+ \\ -1, & x_i \in I^- \end{cases}. \tag{8}$$

- In the image database, to every image I_i that is judged as positive ($f(x_i)>0$) by SVM classifier, a dissimilarity value $D(I_i)$ is calculated. The smaller the $D(I_i)$ is, the closer I_i will approach to the query image. Sort the dissimilarity values of all the judged positive images in ascending order. If the total number of judged positive images is less than N, use the negative images ($f(x_i)\leq 0$) with lowest values of $D(I_i)$ instead until the N images are found. Then return the N images and step into next feedback round and repeat the algorithm until the user satisfies.

In [7], the dissimilarity function $D(I_i)$ is defined as follows:

$$D(I_i) = w_{SVM} D_{SVM}(I_i) + w_{Sim} D^q{}_{Sim}(I_i), \tag{9}$$

$$D_{SVM}(I_i) = \begin{cases} 1/f(x_i), & if \; f(x_i) > 0 \\ e^{-f(x_i)}, & if \; f(x_i) \leq 0 \end{cases}. \tag{10}$$

In (9) and (10), I_i is an image in the database; $D^q{}_{Sim}$ is the same feature similarity measurement function as described in (1); w_{SVM} and w_{Sim} are the weights for D_{SVM} and D_{Sim} respectively, and $f(x_i)$ is the decision hyperplane function in SVM for I_i.

IV. EXPERIMENTS

A. Experimental Environment

To choose the best features combination, a comparison between various combinations will be made in the experiment. And the experiment will also compare the retrieval performance between retrieval only using the best feature combination without relevance feedback and that with relevance feedback. To perform the experiment, 1000 images of 10 semantic categories are chosen, all from the WANG database[1]. The 10 categories are African, beach, buses, dinosaurs, elephants, flowers, food, horses, mountains, and monuments, denoted as Category 1~10 correspondingly. The number of images for each category is 100, and the images are of size 384 × 256 or 256 × 384 pixels. Fig. 2 gives some of the images in each category.

All the experiments are performed on Matlab in Windows Vista operating system with 2 Gbytes of memory. In order to evaluate the performance of the retrieval results, precision [18] is used, which is the ratio of relevant images in the N images returned.

Figure 2. Some images selected from each category.

TABLE III. PARAMETERS SETTING

σ^2	C	w_{SVM}	w_{Sim}	w_{color}	$w_{textuer\text{-}comb}$
0.5	1000	0.3	0.7	0.5	0.5

B. Parameters Selection

In the experiment, the number N of images returned in each retrieval is set 25. Several parameters are preset, including the selection of kernel function and the corresponding parameters from the kernel function and the parameter C in SVM, as well as the weights w_{SVM}, w_{Sim}, w_{color} and $w_{textuer\text{-}comb}$ described in the previous sections. The kernel function chosen in the experiment is RBF kernel as follows:

$$K(x_i, x_j) = \exp\left(-\|x_i - x_j\|^2/\sigma^2\right). \qquad (11)$$

In (11), σ^2 is a kernel parameter. TABLE III gives the parameters used in the experiment. All the parameters are acquired by numbers of tentative experiments and repeated adjustments.

C. Experimental Results

In the first experiment, all the ten image categories are selected to compare the image retrieval performance of different feature combinations described in TABLE II. For each image category, four query images are randomly chosen from the image database. The mean value of precision for the retrieval of the four query images in each category is calculated as the average precision of corresponding category. Fig. 3 is the precision of different feature combinations for each category. Fig. 4 is the average precision for all the three combinations of color and texture features. All the figures indicate that different feature combinations differ in retrieval results. And among the three combinations, features combining color moment, Gabor and wavelet transform texture features give the best retrieval performance. The best combination can achieve a relatively higher precision. However, the overall precision (57%) is still not satisfactory in retrieval applications.

In the second experiment, eight categories are selected to evaluate the effectiveness of using the adopted relevance feedback, and a comparison is made between retrieval only using the best combination of features without relevance feedback and that with relevance feedback. For the latter retrieval way, three rounds of relevance feedback are performed for each query image. For each category, the same four query images chosen in the first experiment are also used in the second experiment. The mean value of precision for the retrieval of the four query images in each category is calculated as the average precision of corresponding category. Fig. 5 is the precision of relevance feedback for each of the eight categories. Fig. 6 describes the average precision for each feedback round. In Fig. 5 and Fig. 6, RF stands for relevance feedback; RF-0 is the initial retrieval only based on the combination of visual features, and RF-1, RF-2 and RF-3 are the first, second, and third relevance feedback respectively. The figures indicate that the adopted relevance feedback can greatly boost the retrieval precision, compared to the retrieval results of only using the best feature combination of color moment, Gabor and wavelet transform features (RF-0 in Fig. 5 and Fig. 6). Besides, compared to the initial retrieval precision (RF-0 in Fig. 6), with the number of feedback increasing, the retrieval performance is improved by about 31.38%, 44.75%, and 46.38% correspondingly, which greatly improves the precision of image retrieval. Fig. 7 is the retrieval results of initial retrieval and relevance feedback using color moment, Gabor and wavelet transform texture features.

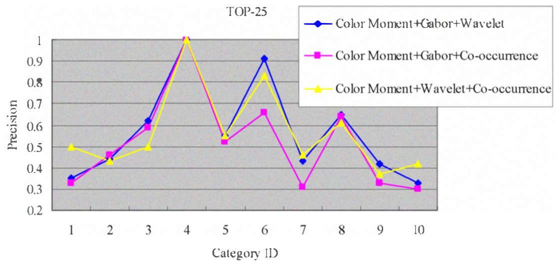

Figure 3. Precision of different combinations of features for each category.

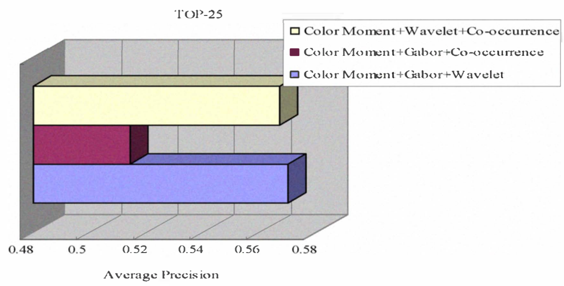

Figure 4. Average precision of different combinations of features.

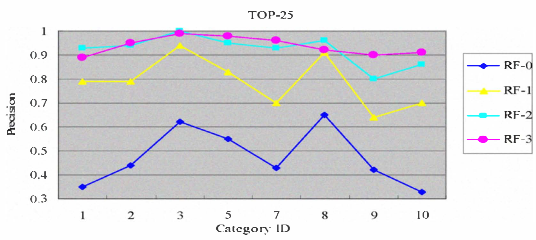

Figure 5. Precision of relevance feedback for each category using color moment, Gabor and wavelet transform features.

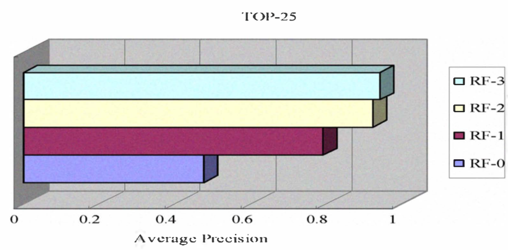

Figure 6. Average precision of relevance feedback using color moment, Gabor and wavelet transform features.

V. CONCLUSIONS AND FUTURE WORK

In the paper, visual features combination of color and texture are used for content-based image retrieval. By comparing different combinations of visual features, an optimal combination of Gabor and wavelet transform texture features which has a relatively better retrieval performance is chosen. However, the overall precision is still not satisfactory. Therefore, relevance feedback mechanism based on SVM and feature similarity is introduced. From the experimental results, SVM and feature similarity based relevance feedback using best feature combination can greatly improve the retrieval precision, and with the number of feedback increasing, the retrieval accuracy is proportionally improved correspondingly

Although the experimental results showed that the proposed method has good retrieval precision, some further studies should be done in the future, which include that the method need to be evaluated further on larger databases and the features to be combined need to be extended to other types of features such as shape and spatial relationship in the future research.

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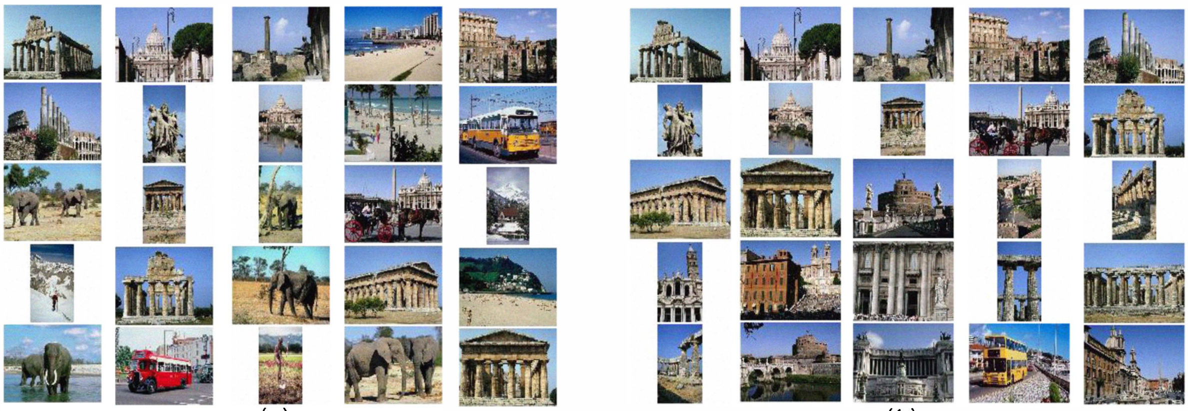

(a) (b)

Figure 7. An example of image retrieval results: (a) is the retrieval result only using color moment, Gabor and wavelet transform features. (b) is the retrieval result after three times of relevance feedback. The upper left image in (a) is the query image.