Content-Based Image Retrieval By Relevance Feedback [*]

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Abstract. Relevance feedback is a powerful technique for content-based image retrieval. Many parameter estimation approaches have been proposed for relevance feedback. However, most of them have only utilized information of the relevant retrieved images, and have given up, or have not made great use of information of the irrelevant retrieved images. This paper presents a novel approach to update the interweights of integrated probability function by using the information of both relevant and irrelevant retrieved images. Experimental results have shown the effectiveness and robustness of our proposed approach, especially in the situation of no relevant retrieved images.

1 Introduction

Content-based image retrieval(CBIR) has become one of the most active research areas in the past few years [1]-[6]. Generally, a set of features (e.g. color, shape, texture, moments, etc.) is extracted from an image to represent its content. Successful content-based image retrieval systems require the integration of various techniques in the fields of image processing and information retrieval [7].

Relevance feedback in information retrieval is an automatic process for query reformulation [8]-[10]. In principle, relevance feedback is based on automatically changing the set of query terms as well as the weights associated with these terms. This is done in order to increase the weights of important query terms and to decrease the weights of unimportant ones. It is accomplished by investigating the set of documents initially retrieved, and increasing the weights of those terms that are in the relevant documents. Experiments show the relevance feedback techniques considerably improve the quality of the term-weighting retrieval system.

Recently, relevance feedback based CBIR techniques have emerged as a promising research direction. MARS [7] introduced both a query vector moving technique and a re-weighting technique to estimate the ideal query parameter. MindReader [11] formulated a minimization problem on the parameter estimation process. Rui et al. [12] present a relevance feedback based interactive retrieval approach, which effectively takes into account the following two distinct characteristic of CBIR systems: the gap between high-level concepts and low-level features, and subjectivity of human perception of visual content. Rui and Huang [13] proposed a novel global optimization framework. Wood, Campbell and Thomas [14] described an image database query system(IDQS), which consisted of a set of radial basic function (RBF) networks.

Most relevance feedback based CBIR techniques have only utilized information of the relevant retrieved images and cannot deal with situations of no relevant retrieved images. They have not made great use of information of the irrelevant retrieved images, especially in the situation of there is less relevant retrieved images than irrelevant retrieved images.

In our opinion, both the relevant retrieved images and the irrelevant retrieved images contain much information of features used. This paper presents a novel update approach for interweights to . It is organized as follows. In section 2, some relevance feedback techniques are introduced. A novel update approach for interweights is proposed in section 3. In Section 4, performance experiments are conducted, and experimental results are discussed. Section 5 gives a conclusion.

2   Overall Similarity Function

Suppose an image databases DB is composed of c training images $\{I_1, I_2, \cdots, I_c\}$. For a query image Q, a retrieval decision can be made according to the overall similarity between Q and any image $I \in DB$. An image contains rich content, such as color, shape, texture and invariant moments of the object in the image, and each of these features(e.g. shape) can be characterized by a feature vector.

Feature Extraction For any image $I \in DB$, a feature extraction function F is defined as

$$F(I) : \Re^{|I|} \to \Re^n \tag{1}$$

where $|\cdot|$ indicates the number of elements of a digital image matrix.

Suppose m feature vectors can be extracted for an image, the similarity for the ith feature between the query image Q and any training image $I \in DB$ can be defined as followings:

$$\Phi_i(I, Q) = (F_i(I) - F_i(Q))^T W_i(F_i(I) - F_i(Q)) \tag{2}$$

where $F_i(I)$ and $F_i(Q)$ are the ith n_i-dimensional image feature vectors of the images I and Q, and W_i are the $(n_i \times n_i)$ intraweight matrix associated with the components of the ith feature vectors. Therefore, the overall similarity function

between the query image Q and any training image $I \in DB$ can be defined:

$$D(I, Q) = \sum_{i=1}^{m} U_i \Phi_i(I, Q) \qquad (3)$$

where U_i are the interweights associated with the ith feature vectors.

The images in the database DB are ordered by their overall similarities to the query image Q. The k most similar ones $\Re = \{R_1, R_2, \cdots, R_k\}$ are returned to the user, where k is the number of images the user wants to retrieve.

Optimization Approach Suppose for any retrieved image $R_j \in \Re$, π_j is the degree of relevance given by user. The following optimization problem was formulated by Y. Hui et al. [12]:

$$\min J = \sum_{j=1}^{k} \pi_j D(R_j, Q) \qquad (4)$$

$$s.t. \begin{cases} \sum_{i=1}^{m} \dfrac{1}{U_i} = 1 \\ \det(W_i) = 1 \\ (i = 1, \cdots, m) \end{cases} \qquad (5)$$

The optimal update for Q_i is

$$\hat{Q}_i = \frac{\sum_{j=1}^{k} \pi_j F_i(R_j)}{\sum_{j=1}^{k} \pi_j} \qquad (6)$$

That is, the ideal query vector for the ith feature is nothing but the weighted average of the retrieved images for the ith feature.

The optimal solutions for W_i is

$$\hat{W}_i = \sqrt[n_i]{\det(C_i)} C_i^{-1} \qquad (7)$$

where $C_i = \sum_{j=1}^{k} \pi_j \Delta_{ij} \Delta_{ij}^T / \sum_{j=1}^{k} \pi_j$, $\Delta_{ij} = F_i(R_j) - F_i(Q)$. The physical meaning of this optimal solution is that the optimal weight matrix is inversely proportional to the covariance matrix of the retrieved images.

The optimal update formula for U_i is

$$\hat{U}_i = \sum_{v=1}^{m} \sqrt{J_v / J_i} \qquad (8)$$

where $J_v = \sum_{j=1}^{k} \pi_j \Delta_{vj}^T W_v \Delta_{vj}$ $(v = 1, \cdots, m)$. This formula tell us, if the total distance J_i of the ith feature is small, this feature should receive high weight and vice versa.

For the interweight updating formula (8), U_i are dealt only with the relevant retrieved images. This formula can not utilize any information of the irrelevant retrieved images, and does not work when all the retrieved images are regarded as irrelevant to the query by the user. This paper intends to make greater use of information of all the retrieved images.

Scoring Approach Suppose for any retrieved image $R_j \in \Re$, the user marks it as highly relevant, relevant, neutral, irrelevant, or highly irrelevant, according to his information need and perception subjectivity. Let $Score(R_j)$ be the relevance score fedback by the user for the jth retrieved image $R_j \in \Re$:

$$Score(R_j) = \begin{cases} 3 & \text{if} \quad \text{highly relevant} \\ 1 & \text{if} \quad \text{relevant} \\ 0 & \text{if} \quad \text{no opinion} \\ -1 & \text{if} \quad \text{irrelevant} \\ -3 & \text{if} \quad \text{highly irrelevant} \end{cases} \tag{9}$$

Let $\Re^{(i)} = \{R_1^{(i)}, R_2^{(i)}, \cdots, R_k^{(i)}\}$ be the set containing the k most similar images to the query Q according to the similarity value $\Phi_i(I, Q)$ for the ith feature. The interweights U_i can be calculated with the following formula [13]:

$$U_i = \sum_{R_j \in \Re^{(i)}} Score(R_j) \tag{10}$$

It is noted that if $U_i < 0$, set it to 0 and the raw weights are needed to be normalized to make the sum of the normalized weights equal to 1.

3   Integrated Probability Function

Based on the posterior probability estimators, King and Jin [15] proposed an integrated probability function, which was successfully used as a new multi-feature combination decision rule in the Chinese cursive script characteristic image retrieval.

Integrated Probability Function The following integrated probability function can serve as the overall similarity function $D(I, Q)$ [15]:

$$D(I, Q) = \frac{\sum_{i=1}^{m} U_i P(F_i(I), F_i(Q))}{\sum_{i=1}^{m} U_i} \tag{11}$$

where $P(F_i(I), F_i(Q))$ is the estimator of the posterior matching probability between image I and image Q on the ith feature, which is determined according to the following formula:

$$P(F_i(I), F_i(Q)) = \frac{1}{c-1}\left(1 - \frac{\|F_i(I) - F_i(Q)\|}{\sum_{v=1}^{c}\|F_i(I_v) - F_i(Q)\|}\right) \tag{12}$$

where $\|\cdot\|$ indicates the common Euclidean distance.

Suppose for any retrieved image $R_j \in \Re$, the user marks it as **relevant**, **neutral**, or **irrelevant** according to his information need and perception subjectivity. Let S be the number of retrieved images in $\Re$ which are relevant to the

query Q and T be the number of retrieved images in $\Re$ which are irrelevant to the query Q.

For the ith feature, Let s_i be the number of retrieved images in $\Re^{(i)}$ which are relevant to the query Q and t_i be the number of retrieved images in $\Re^{(i)}$ which are irrelevant to the query Q.

For the interweight updating formula (10), if the number of highly relevant or highly irrelevant retrieved images is supposed to be 0, U_i are dealt only with s_i and t_i. When S is much smaller than T, s_i have more probabilities to be less than t_i, and therefore U_i will be zero for each $i \in \{1, 2, \cdots, m\}$. For example, suppose that S be 1 and T be 9, then s_i will be in $\{0, 1\}$ and t_i will be in $\{0, 1, \cdots, 9\}$. However, it is easy to understand that in the above example, if for a given i, s_i be 1 and t_i be 2, the ith feature can be said to be more effective than all m features to be used with known interweights, i.e., U_i should be greater than 0, which is assigned according to the existing formula (10).

In our opinion, in order to make greater use of information of all the retrieved images, U_i should be dealt with the ratios of $\dfrac{s_i}{S}$ and $\dfrac{t_i}{T}$. Taking into account the situations of zero relevant retrieved images or zero irrelevant retrieved images, a novel updating formula of raw interweights U_i is presented as follows:

$$U_i(s_i, t_i) = \exp\left\{ \alpha \left(\frac{s_i + 1}{S + 1} - \frac{t_i + 1}{T + 1} \right) \right\} \tag{13}$$

where $\alpha > 0$ is a constant.

Obviously, $U_i(s_i, t_i)$ will increase as s_i increases for a fixed t_i, and will decrease as t_i increases for a fixed s_i. If for any fixed i^{th} feature, $s_i = S$, and $t_i = T$, we have $U_i(S, T) = 1$, which means that the ith feature is as effective as all features. As we know, the exponential function $\exp(\cdot)$ changes slowly on the interval $(-1, 1)$, a large parameter α is needed in the formula (13). The raw weights are needed to be normalized to make the sum of the normalized weights equal to 1.

4   Experimental Results

In this section, we compare the retrieval performance between the proposed method and the scoring method.

There are 10 trademark images with 111×111 resolution [6]. For each trademark image, 10 deformed images and 10 hand draw images can be obtained, and these 21 images can be regarded as to be relevant images. The database is composed of 10 trademark images and their corresponding 10 deformed images for each. All the 110 images in the database DB are shown in Figure 1. In the experiment, we tested our system with 100 hand drawn images, which are divided into 10 groups and indexed from 1 to 100. Figure 2 shows these 100 hand drawn test images.

For an image, seven kinds of features are extracted. They are listed in Table 1. The first four kinds of features are from [6], and the last three kinds of features are computed on 55×55 low resolution images [15].
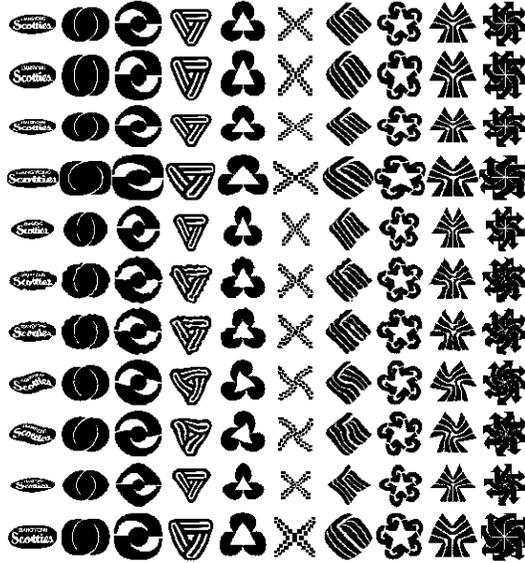
Fig. 1. 110 Images in the Database DB

The retrieval performance is measured using the following average retrieval precision:

$$Precision = \frac{relevant \;\; retrieved}{k} \times 100\% \qquad (14)$$

where $k = 10$ is the number of total retrieved images.

The initial interweights U_i $(i = 1, \cdots, 7)$ are given to be equal. The parameter α is chosen to be 5. The average retrieval precisions for each test group and all the test images are summarized in Table 2. The symbol "rf" denotes how many iterations of relevance feedback.

From Table 2, the average retrieval precision increases from 74.7% to over 90% by relevance feedback techniques. Relevance feedback is a powerful tool for content-based information retrieval. Moreover, the proposed update formula (13) is more effective than the existing scoring formula (10).

For 74 samples out of all 100 test images, the same retrieval performances are obtained with these two methods. For the other 26 samples, two methods obtain different retrieval performances. These experimental results in detail are listed in Table 3.

From Table 3, the proposed novel method is shown to be more robust than the scoring method, especially for 33th sample. Moreover, it can make great use
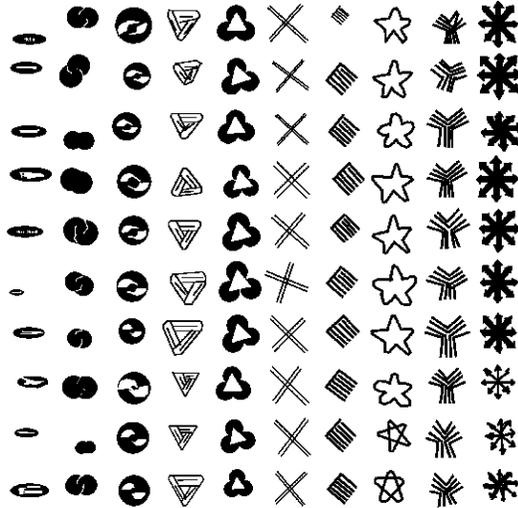
Fig. 2. 100 Hand Drawn Test Images

of information of both relevant retrieved images and irrelevant retrieved images, especially in the situations of no relevant retrieved images.

5 Conclusion

In this paper, a novel relevance feedback technique for updating the interweights has been proposed. Experimental results show that the proposed method outperforms the existing scoring method. Although our database is small, it is convincing that the proposed method can make great use of information of all the retrieved images to the user.

6 Acknowledgement

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Table 1. Seven Kinds of Features for an Image

No.	Description of Feature
1	1-dimensional eccentricity [6]
2	1-dimensional circularity of approximated boundary
3	7-dimensional invariant moment vector
4	63-dimensional Fourier descriptors of approximated boundary
5	36-dimensional pseudo Zernike moment vector $\{Z_{nk}(0 \leq k \leq n \leq 7)\}$ [15]
6	30-dimensional Zernike moment vector $\{Z_{nk}(0 \leq k \leq n \leq 8,\ \text{and}\ n - k = \text{even})\}$
7	25-dimensional Legendre moment vector $\{\lambda_{mn}(0 \leq m, n \leq 4)\}$

Table 2. Average Retrieval Precisions in Percentage for Groups and for DB

Group	0 rf	Scoring 1 rf	Scoring 2 rf	Proposed 1 rf	Proposed 2 rf	Group	0 rf	Scoring 1 rf	Scoring 2 rf	Proposed 1 rf	Proposed 2 rf
1-10	100	100	100	100	100	51-60	100	100	100	100	100
11-20	81	100	100	100	100	61-70	50	97	100	92	100
21-30	17	60	60	63	81	71-80	63	91	92	95	95
31-40	98	94	99	99	99	81-90	78	81	85	87	90
41-50	96	100	100	100	100	91-100	64	77	77	83	85
Average Precision for DB							74.7	90	91.3	91.9	95

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Table 3. Average Retrieval Precisions in Percentage for 26 Samples

Sample	0 *rf*	Scoring		Proposed		Sample	0 *rf*	Scoring		Proposed	
		1 *rf*	2 *rf*	1 *rf*	2 *rf*			1 *rf*	2 *rf*	1 *rf*	2 *rf*
23	0	0	0	0	10	77	60	70	70	80	80
24	0	0	0	10	90	80	60	80	80	90	90
26	0	0	0	20	100	82	80	90	90	70	80
33	90	40	20	90	90	84	90	80	90	100	100
61	60	100	100	90	100	85	50	50	50	60	70
64	50	100	100	90	100	89	50	20	50	70	80
65	30	90	100	80	100	91	30	90	90	80	80
66	60	100	100	90	100	92	20	20	20	60	70
67	50	100	100	90	100	93	20	80	80	70	70
68	50	100	100	90	100	94	80	90	90	100	100
69	30	90	100	80	100	95	80	80	80	90	90
74	70	90	100	100	100	96	80	80	80	90	90
76	30	80	80	90	90	98	80	80	80	90	100
Average Precision for these 26 Samples							50	69.2	71.1	75.8	87.7

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