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An Image Retrieval Algorithm Based on Reselect Manifold Ranking

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Abstract: Content-Based Image Retrieval (CBIR) has become one of the most active research areas. Researchers focus on introducing manifold learning method into CBIR due to its advantage of learning user's semantic conception. In this paper, we review the existing image retrieval algorithms based on manifold ranking and studied the issues of them. Particularly, we propose a novel image retrieval algorithm based on reselect manifold ranking to save online response time and improve the precision for image retrieval. The experimental results on image database demonstrate the effectiveness of our proposed algorithm.

Keywords: manifold ranking; content-based image retrieval; CBIR; manifold learning

1 Introduction

Content-based image retrieval (CBIR) is widely used to retrieval images by their visual content, such as color, texture, shape and so on. It can effectively overcome the weak points (*e.g*: need much manual annotation, existing inconsistency annotation in same image etc) of traditional keywords based image retrieval. Recently, the study of CBIR has been a topic of growing interest [1~3]. Even so, because images are always represented by visual feature, semantic gap, which is the gap between the low-level visual features and the high-level user semantic, seriously limits the improvement of CBIR performance. Furthermore, since an image contains many semantics and different users have different understanding on the same image. It is difficult to meet users' requirements relying solely on visual feature of image. Relevance feedback (RF) [4], which is introduced from information retrieval, has been demonstrated to be a powerful tool which involves the user in the loop to enhance the performance of CBIR. Although it is a reasonable solution theoretically, the limitation of user's patience will result that less information is feed backed into the system. Hence, how to obtain the users' semantic with small amount of feedback become a critical issue to be solved.

In addition, the similarity metrics between images are very important equally. The existing metrics are generally based on pair-wise distance calculation. However, some studies [5] showed that high dimensional data such as image usually exists in a low dimensional manifold, so simply pair-wise distance can't reflect the really distances between images. A series of experiment results [6~12] verified that image retrieval based on manifold assumption can improve the image retrieval performance. Motivated by this, this paper focuses on introducing image retrieval combining *manifold ranking* with *relevance feedback*, and thus get higher precision for image retrieval and consume shorter online response time.

The rest of this paper is organized as follows. First, we investigated research status and issues of image retrieval based on manifold ranking. Section 3 gives the detail description of our proposed algorithm. A series of experimental results are discussed in Section 4 and we conclude this paper in Section 5.

2 Related Works

Manifold ranking (MR) [13] algorithm is a ranking algorithm which ranks the data with respect to the intrinsic manifold structure collectively revealed by a great amount of data. He et al. [6,7] introduced MR algorithm into image retrieval, and proposed manifold-ranking based image retrieval (MRBIR) to improve image retrieval performance. After that, image retrieval based on MR has gained much attention. Wan et al. [8] used image block instead of the whole image as the unit in the manifold-ranking process, and the retrieval score of each image is the fusion of the blocks' ranking scores of the blocks. Liu et al. [9] proposed a human behavior consistent relevance feedback model based on MR for image retrieval, and designed different methods for each human behavior to refine the users' query and regulate the similarity metric based on user's relevance feedback. Cui et al. [10] proposed a method combined with manifold learning and incorporate clustering. Li et al. [11] introduced MR to visual feature and keyword space for image retrieval, and combined these to learning user's semantic space.

These existing algorithms based on MR are mostly

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used MRBIR framework or its extends, firstly, it needs to calculate a $n \times n$ weight matrix S(n is the number of images in database) based on the distance of all images in database, then uses S to calculate final ranking scores f, or uses formula to compute f based on unit matrix minus S. However, no matter in what way, it involves a number of operations on a large matrix, which cost too much retrieval time when such algorithms are applied to a large number of image database. So He et al. [12] proposed a fast manifold ranking algorithm to save time in math view way, but it only saves time in computing inverse of matrix and doesn't solve search time issue really.

After investigating the aforementioned solutions, we find that there still exist some issues to be solved for large-scale database.

(1) Calculating similarity values of dissimilar images wastes much time. Because these algorithms must calculate similarity values for all images (including images that user doesn't interest) based on the entire image database in each retrieval round. It is impractical that when the image database is too large, this way costs much long time to search.

(2) MRBIR algorithm is difficult to select appropriate K. This algorithm is based on the assumption that the data points lie in the manifold structure, and uses KNN to approximate the manifold structure, then inappropriate choice of K would lead to deterioration of search results. When we calculate f by formula, we need to compute the inverse of a large matrix whose number of non-zero element is related with K. Hence, if K values too small, it may lead to matrix singular. On the other hand, too large K may make many dissimilar points to be semantic neighbors, and result in the degradation of algorithm performance.

(3) Relevance feedback is not used to improve performance adequately. Because the ultimate search results are impacted by KNN, so we can utilize user feedback to further correct KNN to enhance retrieval performance.

Our goal in this paper is to solve the issues mentioned above, and we propose a novel image retrieval algorithm based on reselect manifold ranking (IRBRMR). Compare to MRBIR, our algorithm can get more significant improvement in both precision and online response time.

3 Image Retrieval Algorithm Based on Reselect Manifold Ranking

The core idea of IRBRMR is to select some similar images before applying MR algorithm to search. In details, we apply MR to the most relevant images that choose from database instead of all images in the image database, so only part of images in database whose similarity value need to be calculated. This method can gain the same or even higher precision while saving online response time. The Summary flow chart of IRBRMR is illustrated as Fig. 1. The most relevance images, which are selected based on search sample or feedback relevance image, are termed as Search Candidate Image Set(SCIS) in this paper.

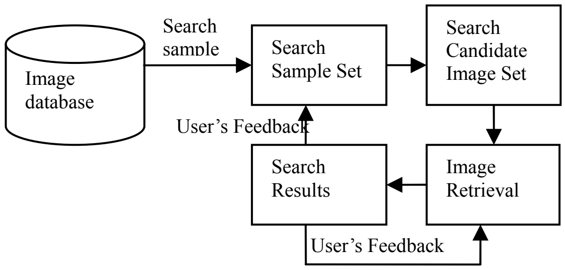

Figure 1. Summary flow chart of IRBRMR algorithm

3.1 Algorithm Description

Fig. 1 gives the overall framework of the retrieval method proposed in this paper. The key problem of this framework is how to choose those images which are consistent with users' semantic, and how to use user feedback to further improve the image retrieval performance.

To descript the algorithms, we represent all images in database as $X = \{x_1, x_2, ..., x_n\}$, search sample set as $Q = \{q_1, q_2, ... q_m\}$, search candidate image set as $X' = \{x_1, x_2, ..., x_N\}$, their relationships are $Q \subset X' \subset X$, defining vector $y = [y_1, y_2, ... y_N]^T$, $y_i \in \{-\beta, 0, 1\}$, $\beta \in [-1, 0)$, vector $f = [f_1, f_2, ..., f_N]^T$. For the user feedback, we assume that all relevant images composed set R, irrelevance images composed set I. Our objective is to calculate the relevance value f_i of every image x_i in X' based on the known X and Q. Detailed description of the algorithm is as following:

(1) Choose SCIS based on image sample set which are composed of image sample and relevance images feedback from user.

(2) Create a KNN map according to search candidate image set. Taking each image as a vertex, then compute the most K adjacent images for each image, and create a connection between images with their K adjacent images.

(3) If there is user feedback, then correct KNN; otherwise, skip this step. Firstly, add images, which belong to R, into search sample set Q, then for every image $x_i \in I$, if there exists a connection between x_i and x_j in KNN, $x_j \in Q$, then get rid of this connection.

(4) Compute the edge's weight value between x_i and x_j in KNN according to formula (1), if there don't exist an edge between x_i and x_j, then W_{ij}=0, especially W_{ii}=0.

$$W_{ij} = \exp[-d^2(xi, xj) / 2\sigma^2] \quad (1)$$

(5) Normalize W to S according to formula (2),

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where $D_{ii} = \sum_j W_{ij}$.

$$S = D^{-1/2} W D^{-1/2} \tag{2}$$

(6) Iterative calculate the final similarity value f^* according to formula (3), where $\alpha \in [0,1)$, element y_i in vector y corresponds to image x_i in search sample set Q and set I. If $x_i \in Q$, then y_i=1; else if there exist user feedback, and $x_i \in I$, then y_i=- β ; otherwise, y_i=0. The parameter β is used to adjust the degree of the positive and negative feedback affecting results.

$$f(t+1) = \alpha S f(t) + (1-\alpha) y \tag{3}$$

Referred to paper [3], f^* can be computed by formula (4).

$$f^* = (1-\alpha)(I - \alpha S)^{-1} y \tag{4}$$

(7) Return the top largest images to user by relevance value f^*.

(8) If user doesn't satisfy with the current results, and then tag relevance and irrelevance images as feedback to system, and go to (1), until user satisfies with the query results.

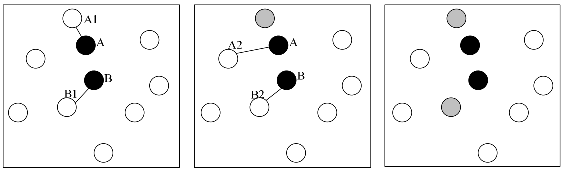
In practical applications, users maybe feel impatient when they are always asked to tag images. So we adopt the way of implicit feedback, that is, if users click an image, then it is possible that users are interesting in this image. So we can take this image as relevance image, and remainder images which are not clicked as irrelevance image. When users explore next page, we can take this information as users' feedback return to system and system use this information to further learn users' semantic, and return search results. In this way, users will get search results that they are interested without doing extra work.

3.2 Choice of Search Candidate Image Set

The aim of choosing SCIS based on the search sample set is to reduce user's online response time. At the beginning, search sample set is only composed by search samples provided by users. Once feedback occurs, we can add relevance images from users' feedback into search sample set.

The way of choosing SCIS can be described as follows. First, computing the distance of every image in search sample set according to distance metrics. The aim is to get the nearest images of every image in search sample set. Second, selecting the smallest distance of the image with images in search sample set. And repeating the selection until getting the required number of images in SCIS.

As is illustrated in Fig. 2, search sample set elements is denoted as black points. Similarly, the images chose as elements of SCIS is denoted as gray points, the remaining images in database is denoted white point.



(a) (b) (c)

Figure 2. Graph interpretation of selecting SCIS

Assume that there are two images in search sample set, on which we will choose two images to compose SCIS. In Fig.2(a), the point A and B in search sample set has got their most nearest points which are point A1 and B1 respectively. Considering that distance between A1 and A is smaller than that between B1 and B, we choose A1 as search candidate point, and add it into SCIS. Similarly, we choose B2 as search candidate point in Fig.2(b), and the final results are showed in Fig.2(c).

To save time, once we get the most nearest images of every image in first round, we only compute nearest point of the image that has been chose as search candidate image in next round. As the case in Fig.2(b), we only get point A's nearest point A1.

4 Case Study & Performance Analysis

We implement IRBRMR and compare its performance against MRBIR. The image set used here is provided by Wang et al.[14,15], which includes 1000 images from 10 categories, each category includes 100 images. Images are represented by FCTH [16] and distance metric method of FCTH feature between the images use the same method with paper [16]. In our experiment, we set the parameter N=150, K=20, β =0.6 in IRBRMR algorithm, and the parameter of MRBIR algorithm can be referred to paper [6], and the handling of negative feedback through the program using the similarity matrix S in paper[6].

We designed two experiment schemes, we selected 5 images from 10 categories randomly, and total 100 images are selected as query images respectively. In scheme 1, we retrieval 12 images as results in each round, and feedback 8 times, image tagged as relevance one will not appear again. In scheme 2, we retrieval 12 images in the first round, user tagged relevance image as feedback, then retrieval 100 images including images that has tagged as relevance ones.

4.1 Case Study

We give an image's retrieval results in Fig.3, we can find that there are some other categories images which were tagged as irrelevance, then these categories images disappear in next round obviously in IRBRMR, but these categories images still exist in MRBIR. This indicates that IRBRMR has an ideal adaptability to users semantic due to it uses negative feedback to correct KNN map. It is obviously that the results of two algorithms are improved after feedback once, and the results of IRBRMR algorithm are better than that of MRBIR.

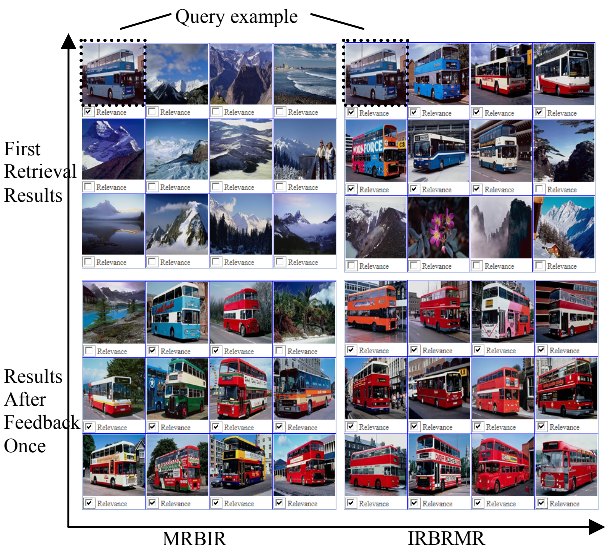


Figure 3. Retrieval result in graph showing

4.2 Performance Analysis

We use online response time, precision-scope curve precision rate, and coverage to evaluate the performance of the image retrieval algorithms.

4.2.1 Online Response time

We compare the average online response time of IRBRMR by experiment schem1, which is listed in Table 1(Intel Pentium Dual T2330 1.60GHz，0.99GB RAM). IRBRMR achieves 54x/60x speedup for online response, and the time to choose SCIS is very small, so we needn't worry about that IRBRMR waste time in choosing SCIS.

Table 1. Comparison of online response time

Time(second)	MRBIR	IRBRMR	Choose SCIS
search	24.276	0.449	0
Feedback	32.130	0.526	0.0081

4.2.2 Precision and Coverage

(1) IRMRBIR with Implicit Feedback

In practical applications, we can use an implicit feedback approach mentioned in Section 3.2, scheme 1 is a simulation of this approach. This way is feasible when most of the images are interested by users in each round. Fig. 4 shows that the precision of IRBRMR algorithm is higher than MRBIR, and its precision is higher than 0.5 in each round, so it indicates that IRBRMR algorithm is feasible using implicit feedback approach.

Experiment results in Fig.4 also illustrate that the precision won't increase with the feedback round, because remainder relevance images in database decrease with the feedback times, and the user feedback

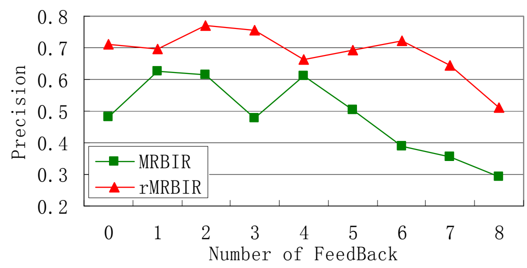


Figure 4. Precision comparison

will not always improve the retrieval results, because when user's feedback contain new knowledge(new relevance images), the algorithms need to further study these knowledge to identify which information is valuable, so the results may appear deteriorate suddenly, and change for the better situation in next round, as is illustrated in Fig.5, these are retrieval results of concrete image sample.

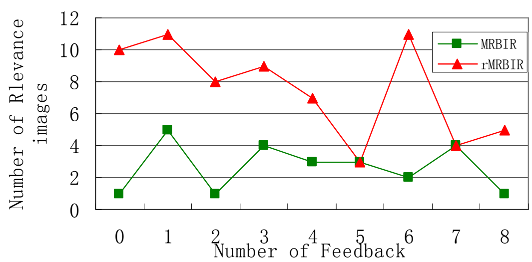


Figure 5. Precision comparison of sample 

Table 2 is the coverage of retrieval result that is the percentage of sum of relevance images in eight round feedbacks by total number of images in category. We can find that the average coverage of IRBRMR is 21.56% higher than MRBIR. The minimize coverage of MRBIR is only 19.00%, but that of IRBRMR is 58%, it mean that IRBRMR can retrieval more relevance images (39) than MRBIR in 100 images when they are in worst-case.

Table 2. Coverage of algorithm contrast

Algorithm name	average	max	min
MRBIR	52.75%	100.00%	19.00%
IRBRMR	74.31%	100.00%	58.00%

(2) IRMRBIR with once feedback

We compare the precision in difference scope by scheme 2, and the results are show in Fig.6. The aim is to compare overall performance evaluation of the algorithms. From the results, we can find that IRBRMR exhibits obviously improvement over MRBIR. Take P20 (the precision within the first 20 retrieved images) as an example, for MRBIR, P10 is 0.673; while for IRBRMR, it is 0.812, which increased about 0.139 than MRBIR.

Fig. 7 is the precision in difference categories getting from scheme 2, the aim is to analyze the fitness of

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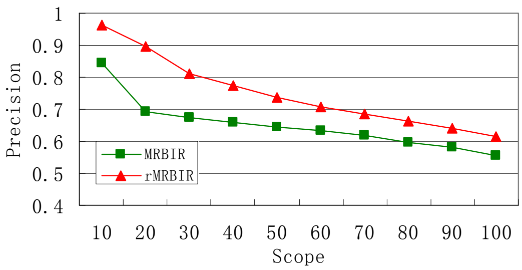
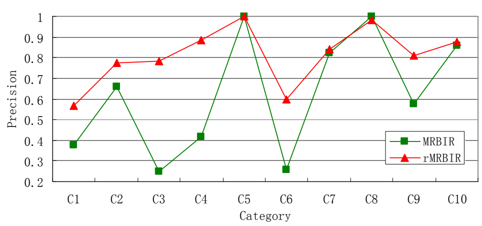


Figure 6. precision comparison after feedback once

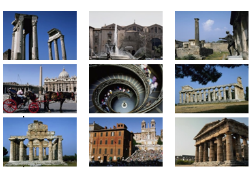
algorithms in difference categories. There are some easy categories, on which all the algorithms perform well. Since the features that we used in our experiments are *FCTH (*Fuzzy Color and Texture Histogram) features, those categories containing images with similar colors and textures which are different from other categories (for example, category 5 in Fig. 7b, category 5 in Fig. 7c) get very good retrieval performance. In category 3(in Fig. 7d) and 5(in Fig. 7e), MRBIR get poor retrieval performance, one reason is that these categories containing images with different colors and textures, and maybe more similar with other categories, for example, the blue sky in images of category 3, it is similar with images in others categories that contain blue sky(e.g. sea view images in category 2 and snow scenery images in category 9), in this situation, if too large parameter k will result in the degradation of algorithm performance, but the k in MRBIR can't be set too small in order to avoid matrix singular(detailed description see Section 3.1), but IRMRBIR hasn't this problem, so IRMRBIR outperforms MRBIR almost in all categories.



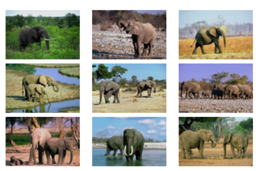
(a)

(b)

(c)



(d)



(e)

Figure 7. precision comparison in different categories (Scope=30)

5 Conclusion

CBIR can retrieval images that are semantically relevant to a query image provided by user, and considering the manifold structure of images' visual feature data can further enhance the performance of CBIR. This paper focuses on the image retrieval algorithms based manifold ranking, and analyzes the issues of existed algorithms, then we proposed reselect manifold ranking image retrieval. IRBRMR can save online response time due to that it reduces the size of matrix in manifold ranking algorithm, and it achieves a significantly higher precision for image retrieval by reselecting relevance image as SCIS based on user's feedback in each round and using user's feedback to correct KNN map. Experiments results establish that the method proposed in this paper can indeed save online response time when it enhances the precision for image retrieval.

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