Navigation Based Relevance Feedback in Content Based Image Retrieval

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Abstract

Accuracy enhancement of Content Based Image Retrieval (CBIR) systems as well as reduction in semantic gap can be effectively achieved with the help of Relevance Feedback. Many schemes and techniques of relevance feedback exist with many assumptions and operating criteria. This paper focuses on a novel method, Navigation-Pattern-based Relevance Feedback (NPRF), which can be used to achieve high efficiency and effectiveness of CBIR while coping with the large-scale image data. By using NPRF method, high quality of image retrieval in RF can be achieved in as small a number of feedbacks as possible. NPRF mainly applies data mining techniques to mine the navigation patterns from the user log information and incorporates the same with the searching for the relevant images.

Keywords: Content based image retrieval, relevance feedback, feature vector, query point, mars.

1. Introduction: An image retrieval system is a computer based system for browsing, searching and retrieving images from a large database containing digital images [1]. Content based image retrieval (CBIR) is the application of computer vision to the image retrieval problem. The search makes use of the contents of the images themselves, rather than relying on only on human input metadata such as captions or keywords.

Relevance Feedback contributes the process of refining the results returned by the CBIR system in a given iteration of an interaction session. The user performs some sort of evaluation over these results returned by the system. This evaluation is fed back to the system.

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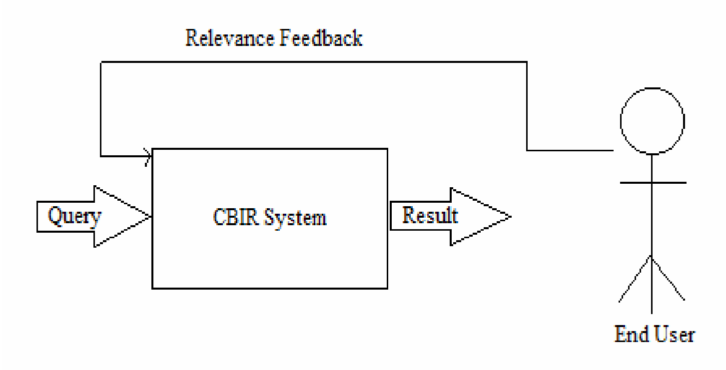

Fig1. Relevance Feedback in CBIR

A CBIR system using relevance feedback basically consists of four components, namely user interface, offline learning, data storage and online learning.

- The user interface allows the user to perform query initially, mainly either by typing keywords, through sketching or by providing an example image. It also allows the user to indicate the relevance of result images, often in the form of one relevant-neutral-irrelevant images.
- In the offline learning phase, image descriptors (features) are extracted from all images in the database. It is very important to select the most useful image descriptors to help narrow the semantic gap because users think in terms of high-level semantic concepts and not in low level image features as available to the system.
- The data storage component acts as virtual system and is responsible for storing and loading of necessary data. It is important to use suitable multi-dimensional indexing techniques for a nearly accurate search in high-dimensional feature space, especially considering that performance quickly suffers with an increase in dimensionality.
- The online learning component performs the actual relevance feedback through interaction with the user. It discovers which image features the user seems relevant and which not and consequently ranks the images according to how well they conform to the relevant features.

In the past, RF has been used in mainly three ways: Probabilistic (Bayesian), Query-Vector Modification (QVM) and Feature Re-weighting [5], but recently lot of research have been focused on improving the efficiency of Relevance Feedback such as Log based, Navigation based, Feature-adaptive relevance feedback (FA-RF) [2].

2 Navigation-based Relevance Feedback Technique

Navigation-Pattern-based Relevance Feedback (NPRF) [6] is an efficient method to achieve high efficiency and effectiveness of CBIR in coping with the large-scale image data. In terms of efficiency, the iterations of feedback are reduced substantially by using the navigation patterns discovered from the user query log. In terms of effectiveness, NPRF makes use of the discovered navigation patterns and three kinds of query refinement strategies, Query Point Movement (QPM), Query Reweighting (QR), and Query Expansion (QEX), to converge the search space toward the user's intention effectively. By using NPRF method, high quality of image retrieval on RF can be achieved in a small number of feedbacks.

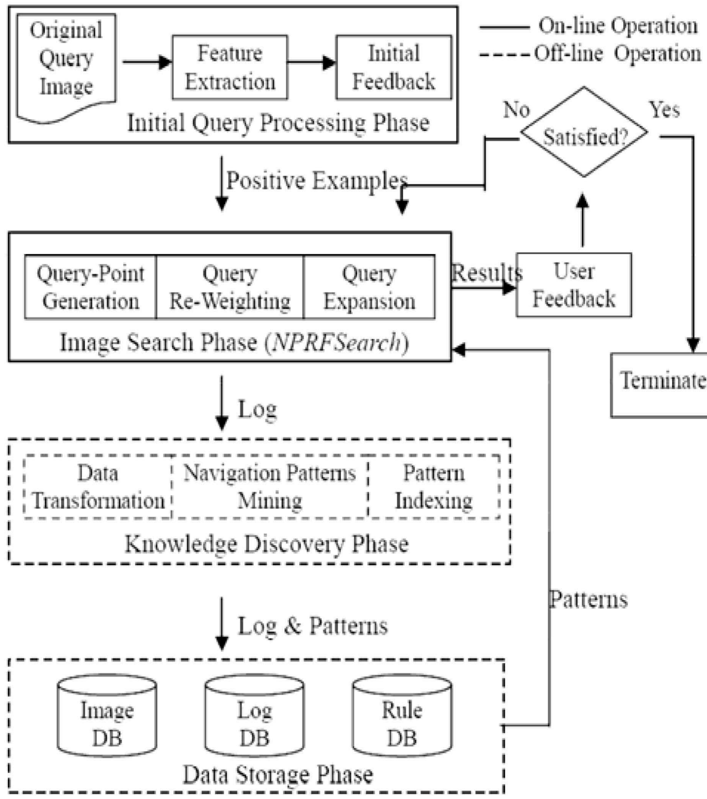

Fig.2 Architecture of NPRF[7]

The task of NPRF approach can be divided into two major operations, namely offline knowledge discovery and online image retrieval.

3 Online Image Retrieval

- **Initial Query Processing Phase:** Without considering the feature weight, this phase extracts the visual features from the original query image to find the similar images. A few and the good examples picked up by the user are further

analyzed into feedback.

- **Image Search Phase:** In this phase, a new query point at each feedback is generated by the preceding positive examples. Then, the k-nearest images to the new query point can be found by expanding the weighted query [8]. The search procedure does not stop unless the user is satisfied with the retrieval results.

4. **On the Knowledge Discovery**

- **Knowledge Discovery Phase:** Learning from user's behaviors in image retrieval can be viewed as one type of knowledge discovery. Consequently, this phase primarily concerns the construction of the navigation model by discovering the implicit navigation patterns from users' browsing behaviors. This navigation model can provide image search with a good support to predict optimal image browsing paths.

- **Data Storage Phase:** The databases in this phase can be regarded as the knowledge marts of a knowledge warehouse, which store integrated, time-variant and nonvolatile collection of useful data including images, navigation patterns, log files, and image features. The knowledge warehouse is very helpful to improve the quality of image retrieval. Note that the procedure of constructing the databases from the image databases can be conducted periodically to maintain the validity of the proposed approach.

Basically, navigation pattern discovery consists of two stages: data transformation and navigation patterns mining. The aim of data transformation is to generate Query Point Dictionary (QPD) to reduce the kinds of terms in the transaction. In this phase, the transformed log table is generated by the logged query sessions containing query session id, iteration number, positive images, and visual query point number. Once a query point is projected onto the QPD, the referred item number is stored into the transformed log table.

As shown in Fig. 3, the transformed log table has to be further partitioned into three tables for various needs in this paper, including QP table, Navigation transaction table, and Partitioned Log table. Navigation transaction table is used for navigation patterns mining. QP table and Partitioned Log table are necessary for image search discussed at length in subsequent sections. In viewing the complete data, the joint data table can be derived with connecting the original attributes of different tables.

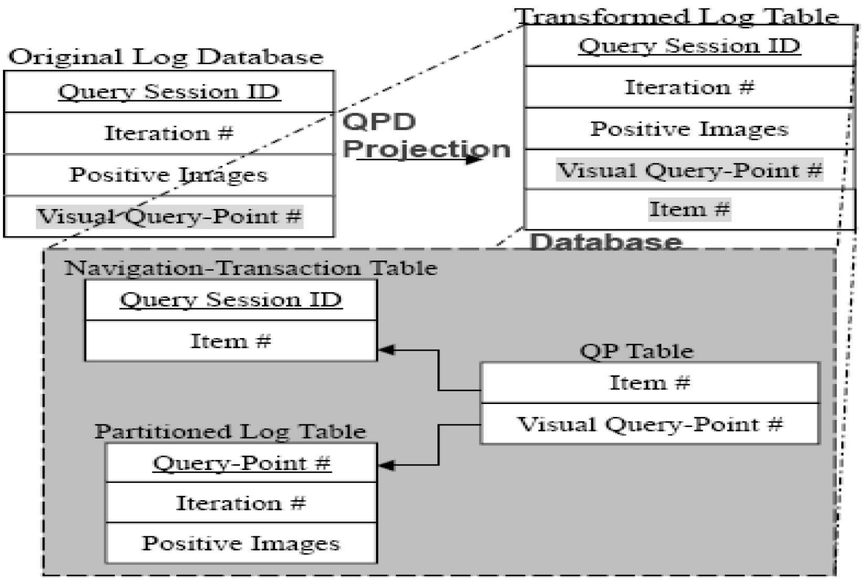

Fig 3. The data model of partitioning log data.

Navigation pattern mining stage focuses on the discovery of relations among the users browsing behaviors on RFB. Basically, the frequent patterns mined from the user logs are regarded as the useful browsing paths to optimize the search direction on RF. User common interests can be represented by the discovered frequent patterns (also called frequent item sets). Through these navigation patterns, the user's intention can be precisely captured in a shorter query process.

The task for establishing the navigation model can be decomposed into two steps:

Step 1: Construction of the navigation transaction table. In Table 1, a query session can be considered a transaction. In this case, the transaction is composed of a query item {C_{1m}, C_{1m} Q} where Q contains the set of starting query images selected to different navigation steps, and several relation items. To exploit valuable navigation patterns, all query sessions in the transformed log table are collected as the navigation transaction table.

Query Session ID	Item
001	C_{11}, C_{21}, C_{32}, C_{42}
002	C_{11}, C_{23}, C_{32}, C_{42}
003	C_{12}, C_{21}, C_{32}, C_{41}
004	C_{12}, C_{21}, C_{31}, C_{42}
005	C_{13}, C_{22}, C_{32}, C_{43}

Table 1. Example of Navigation-Transaction Table

Step 2: Generation of navigation patterns. This operation concentrates on mining valuable navigation patterns to facilitate online image retrieval. For example, as shown in Table 2,

he sequential navigation pattern{C11 → C32 → C42} derived from frequent item set {C11,C3,C42} when minimum support2.

Items	Count	Frequent-item set
C_{11}	2	Frequent1 item set
C_{12}	2	
C_{21}	3	
C_{32}	4	
C_{42}	3	
C_{11},C_{32}	2	Frequent2 item set
C_{11},C_{42}	2	
C_{12},C_{21}	2	
C_{11},C_{32},C_{42}	2	Frequent3 item set

Table2 Example of Navigation Patterns

5.Online Image Search Phase: Aim of search strategy is to tackle the weakness of the traditional approaches, including redundant browsin g and exploration convergence. These unsolved problems result large limitation in RFA lso expensive computation cost make it in practical real applications his tead,NPRF attempt to approximate the optimal solution, namely NPRF Search, to resolve suc h problems by using the generated navigation patterns For the problem of exploration convergence, NPRF approach extends the search range from a query point to a number of relevant navigation paths. As a result, each iterative search can escape from the local optimal space and further move toward reach the global optimal space of the user's interest. For the problem of redundant browsing, the discovered navigation patterns are adopted as the shortest paths to derive the superior results at short feedback process. Additionally the expensive navigation cost is saved further, especially for the massive image data. In general, the NPRF Search algorithm can be recognized as a very important part of our proposed iterative solution to RF, which merges QEX,QPM and QR strategies.

NPRF Search is proposed to reach the high precision of image retrieval at short query process by using the valuable navigation patterns. NPRF Search algorithm is triggered by receiving:

1)A set of positive examples G and negative examples N determined by the user at the preceding feedback.

2)A set of navigation patterns TR={t1,t2,... tn} where each tn contains query seed tn and several patterns (e.g.,C11,C32,C42) for tree, the iterative search procedure can be decomposed into several steps as follows:

1. Generate a new query point by averaging the visual features of positive examples.
2. Find the matching navigation pattern trees by determining the nearest query seeds (root).
3. Find the nearest leaf nodes (terminations of a path) from the matching navigation

pattern trees.

4. Find the top relevant visual query points from the set of the nearest leaf nodes.
5. Finally, top k relevant images are returned to the user.

From the aspect of NPRFSearch, step 1 can be regarded as QPM and steps 2-5 can be regarded as QEX. By looking at a large number of query transactions, most queries can be well answered from matching users' interests by NPRFSearch.

6. Advantages and Issues of NPRF

Advantages:

1. By using NPRF method, high quality of image retrieval in RF can be achieved in a small number of feedbacks. The experimental results reveal that NPRF outperforms other existing methods significantly in terms of precision, coverage, and number of feedbacks.
2. This method provides optimal solution to resolve the problems existing in current RF, such as redundant browsing and exploration convergence.
3. NPRF efficiently optimizes the retrieval quality of interactive CBIR.
4. Within a very short term of relevance feedback, the navigation patterns can assist the users in obtaining the global optimal results.

Issues:

1. User's profile needed to be integrated into NPRF to further increase the retrieval quality which is not yet integrated.

2. In view of very large database, techniques would need parallel and distributed computing techniques which are also not yet introduced.

Comparison Points	**NPRF**	**RF(QPM and QEX)**
No of feedback	2	5-6
Average Accuracy	0.85	0.61-0.66
Average Recall	0.2	0.1-0.15
Time Cost	11.76sec	55-65sec

Table 3: Comparison of NPRF and RF

7. Conclusions

CBIR with relevance feedback strategies has the potential to be at the forefront of the technological improvement, inducing the paradigm of learning for a brand new generation of interactive applications.

To deal with the long iteration problem of CBIR with RF, NPRF can be used for integrating the navigation pattern mining and a navigation-pattern-based search approach named NPSearch. On one hand, the navigation patterns derived from the users' long-term browsing behaviors are used as a good support for minimizing the number of user feedbacks. On the other hand, the algorithm NPRFSearch performs the navigation-pattern-based search to match the user's intention by merging three query refinement strategies. As a result, traditional problems such as visual diversity and exploration convergence are solved.

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