Relevance Feedback for Content-Based Image Retrieval by Mining User Navigation Patterns

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ABSTRACT
This paper presents a novel method, Navigation-Pattern-based Relevance Feedback (NPRF), to achieve the 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, our proposed search algorithm NPRF Search 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. The experimental results reveal that NPRF outperforms other existing methods significantly in terms of precision, coverage, and number of feedbacks.

Keywords: Content based image retrieval (CBIR), Query Point Movement (QPM), Query Expansion (QEX), Query Reweighting (QR), Navigation-Pattern-based Relevance Feedback (NPRF)

1. INTRODUCTION
In the early years of research in CBIR, the focus was on query by visual example (QBVE) [8] a search session begins by presenting an example image (or sketch) to the search engine as a visual query, then the engine returns images that are visually similar to the query image. More recently, the concept of semantic gap has been extensively used in the CBIR research community to express the discrepancy between the low-level features that can be readily extracted from the images and the descriptions that are meaningful for the users.

When searching more generic image databases, one way of identifying what the user is looking for in the current retrieval session (the target of the user) is by including the user in the retrieval loop. For this, the session is divided into several consecutive rounds; at every round the user provides feedback regarding the retrieval results, e.g. by qualifying images returned as either "relevant" or "irrelevant" (relevance feedback (RF) [1], [2], [3], [4] in the following); from this feedback, the engine learns the visual features of the images and returns improved results to the user. The RF [1], [2], [3], [4] mechanism implemented in a search engine should attempt to minimize the amount of interaction between the user and the engine required for reaching good results.

2. EXISTING SYSTEM
A number of powerful image retrieval algorithms have been proposed. Content-Based Image Retrieval (CBIR) is the mainstay of current image retrieval systems. In general, the purpose of CBIR is to present an image conceptually, with a set of low-level visual features such as colour, texture, and shape. These conventional approaches for image retrieval are based on the computation of the similarity between the user’s query and images via a query by example (QBE) [8] system. Despite the power of the search strategies, it is very difficult to optimize the retrieval quality of CBIR within only one query process. To solve such problems, in the QBE [8] system, the users can pick up some preferred images to refine the image explorations iteratively. The feedback procedure, called Relevance Feedback (RF), repeats until the user is satisfied with the retrieval results. Although a number of RF studies have been made on interactive CBIR, they still incur some common problems, namely redundant browsing and exploration convergence.

Relevance feedback refers to a set of approaches learning from an assortment of users' browsing behaviours on image retrieval. Some earlier studies for RF make use of existing machine learning techniques to achieve semantic image retrieval, including Statistics, EM, KNN, etc. Although these forerunners were devoted to formulating the special semantic features for image retrieval, e.g., Photobook [9], QBIC [1], VisualSEEK [2] there still have not been perfect descriptions for semantic features. This is because of the diversity of visual features, which widely exists in real applications of image retrieval. Therefore, active query refinement,
based on the analysis of usage logs, attracts researchers’ attention in this area of RF.

3.PROPOSED SYSTEM

We propose a novel method named Navigation-Pattern-based Relevance Feedback (NPRF) [10] to achieve the high retrieval quality of CBIR with RF by using the discovered navigation patterns. The navigation patterns mined from the user query log. According to the discovered patterns, the users can obtain a set of relevant images in an online query refinement process. Thus, the problem of redundant browsing is successfully solved. The proposed navigation-pattern-based search algorithm (NPRF Search) merges three query refinement strategies, including Query Point Movement (QPM) [7], Query Reweighting (QR) [5], and Query Expansion (QEX) [6], to deal with the problem of exploration convergence. In short, the discovered navigation pattern in NPRF Search can be regarded as an optimized search path to converge the search space toward the user’s intention effectively.

![Diagram](image)

**Fig. 1. System Architecture**

4.NPRF SEARCH ALGORITHM [10]

Input: A set of positive examples \( G = \{g_1, g_2, ..., g_n\} \) picked up by the user, a set of negative examples \( N = \{n_1, n_2, ..., n_m\} \), a set of negative patterns \( TR = \{tr_1, tr_2, ..., tr_n\} \) with the referred query-seed set \( Q = \{q_1, q_2, ..., q_m\} \), and an accurately threshold \( thrd \);

Output: A set of relevant images \( R \);

Algorithm: NPRF search

1. generate a new query point \( q_{\text{new}} \) by \( G \) and compute the new feature weight by equation 3;
2. let \( \text{NIMG} \) be the accumulated set of negative examples and \( \text{NIMG} = \text{NIMG} \cup N \);
3. store \( q_{\text{new}} \) and \( G \) into log database;
4. initialize each \( trh. rth. \text{chk} = 0 \) and \( \text{CanPnt} = \emptyset \);
5. for each \( gt \in G \) do
6. determine the special query-seed \( rth \) with the shortest distance to \( gt \); \( rth \in Q \);
7. \( rth. \text{chk} = 1 \);
8. end for
9. \( \text{if } \frac{|G|}{|G| + |N|} < \text{thrd} \) then
10. for each \( nu \in N \) do
11. determine the special seed \( rth \) with the shortest distance to \( nu \) where \( rth \in Q \) and \( Q \subseteq TR \);
12. \( \text{count}(rth)++ \);
13. end for
14. find the seed \( rth \) with \( \max(\text{count}(rth)) \);
15. \( rth. \text{chk} = 0 \);
16. end if
17. for each \( trh \) do
18. if \( trh. rth. \text{chk} = 1 \) then
19. find the set of the visual query points \( QPT \) within the leaf node of pattern \( trh \);
20. \( \text{CanPnt} = \text{CanPnt} \cup QPT \);
21. end if
22. end for
23. find the top \( s \) visual query point \( SQPT = \{sqpt_1, sqpt_2, ..., sqpt_s\} \) similar to \( q_{\text{new}} \) from \( \text{CanPnt} \);
24. for \( i = 1 \) to \( s \) do
25. find the positive image set \( RIMG \) in the transformed log table, which is referred to \( sqpt_i \);
26. \( \text{CanImg} = \text{CanImg} \cup RIMG; /* \text{CanImg} \) indicates the set of the relevant images */
27. end for
28. \( \text{CanImg} = \{\text{CanImg} \setminus \text{NIMG}\} \);
29. rank the images in \( \text{CanImg} \);
30. return the set of top \( k \) similar images \( R \);

5.MODULES

A. Query Processing
B. Image Searching
C. Knowledge Discovery
D. Data storage

A. QUERY PROCESSING

In this module we extract the visual features from the original query image to find the similar images. Afterward, the good examples (also called positive examples) picked up by the user are further analysed at the first feedback (also called iteration 0).
C. Knowledge Discovery

In this module we primarily concern the construction of the navigation model by discovering the implicit navigation patterns from users’ browsing behaviours. This navigation model can provide image search with a good support to predict optimal image browsing paths. The knowledge warehouse is very helpful to improve the quality of image retrieval. Note that the procedure of constructing rule base from the image databases can be conducted periodically to maintain the validity of the proposed approach.

Fig 2. Query processing

B. IMAGE SEARCHING

In this module, 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. The search procedure does not stop unless the user is satisfied with the retrieval results.

Fig 3. Image Search

Fig 4. Knowledge Discovery
D. DATA STORAGE
The databases in this phase can be regarded as the knowledge marts of a knowledge warehouse, which store integrated, time-variant, and non-volatile collection of useful data including images, navigation patterns, log files, and image features.

Fig 5. Data Storage

Table 1. Compared Approach

<table>
<thead>
<tr>
<th>Compared Approach</th>
<th>Minimum Number of feedbacks</th>
</tr>
</thead>
<tbody>
<tr>
<td>QR</td>
<td>~6</td>
</tr>
<tr>
<td>QPM+QR</td>
<td>5</td>
</tr>
<tr>
<td>QEX+QR</td>
<td>6</td>
</tr>
<tr>
<td>NPRF</td>
<td>2</td>
</tr>
</tbody>
</table>

6. CONCLUSION
To deal with the long iteration problem of CBIR with RF, we have presented a new approach named NPRF by integrating the navigation pattern mining and a navigation-pattern-based search approach named NP Search. In summary, the main feature of NPRF is to efficiently optimize the retrieval quality of interactive CBIR. On one hand, the navigation patterns derived from the users’ long-term browsing behaviours are used as a good support for minimizing the number of user feedbacks. On the other hand, the proposed algorithm NPRF Search 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. For navigation-pattern-based search, the hierarchical BFS-based KNN is employed to narrow the gap between visual features and human concepts effectively. In addition, the involved methods for special data partition and pattern pruning also speed up the image exploration. The experimental results reveal that the proposed approach NPRF is very effective in terms of precision and coverage. Within a very short term of relevance feedback, the navigation patterns can assist the users in obtaining the global optimal results. Moreover, the new search algorithm NPRF Search can bring out more accurate results than other well-known approaches. In the future, there are some remaining issues to investigate. First, in view of very large data sets, we will scale our proposed method by utilizing parallel and distributed computing techniques. Second, we will integrate user’s profile into NPRF to further increase the retrieval quality. Third, we will apply the NPRF approach to more kinds of applications on multimedia retrieval or multimedia recommendation.

REFERENCES
Very Large Data Bases (VLDB), pp. 218-227, 1998.

