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A Comprehensive Review of Recent Relevance Feedback Techniques in CBIR

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***Abstract*—Accuracy enhancement of Content Based Image Retrieval System as well as reduction in semantic gap can be efficiently achieved with the help of Relevance Feedback. Many schemes and techniques of relevance feedback exist with many assumptions and operating criteria. In this paper, we have given a brief overview of recent techniques used for implementing relevance feedback in CBIR. This paper also discusses some of the key issues involved in the adaptation of existing image retrieval techniques to build useful systems that can handle real-world data as well as the advantages of each technique.**

***Index Terms*—Content based image retrieval, relevance feedback, feature vector, query point, itemset.**

I. INTRODUCTION

An image retrieval system is a computer-based system for browsing, searching and retrieving images from large databases 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 only on human-inputted metadata such as captions or keywords.

Relevance Feedback constitutes 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 the results returned in the last iteration and this evaluation is fed back to the system [9].

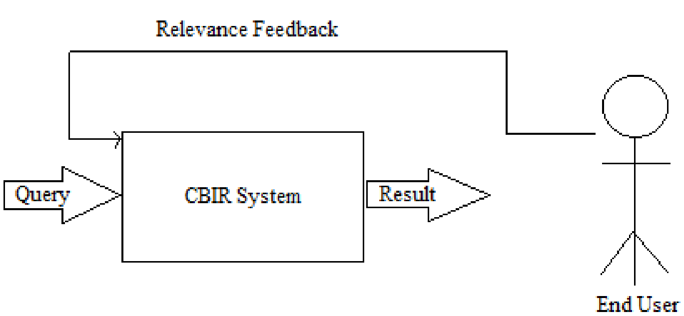

Fig. 1. Relevance Feedback in CBIR

A CBIR system using relevance feedback basically consists of four components, namely user interface, offline learning, data storage and online learning [3][1].

- 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 resultant images, often in the form of nonrelevant-neutral-relevant 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 a virtual file 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].

II. Recent Relevance Feedback Techniques

A. Unified Log Based Relevance Feedback

Unified Log Based RF is an extension of traditional Log based technique used for relevance feedback. Generally a CBIR system can collect and store user's relevance feedback information in a history log. An image retrieval system should take advantage of the log data of user's feedback to enhance its retrieval performance. A unified log-based relevance feedback [6] is a technique that integrates the log of feedback data into the traditional relevance feedback schemes to learn effectively the correlation between low-level image features and high-level concepts.

This method computes the relevance information between query images and images in the database using both the log data and the low-level features of images and combine them to produce a more accurate estimation of relevance score.

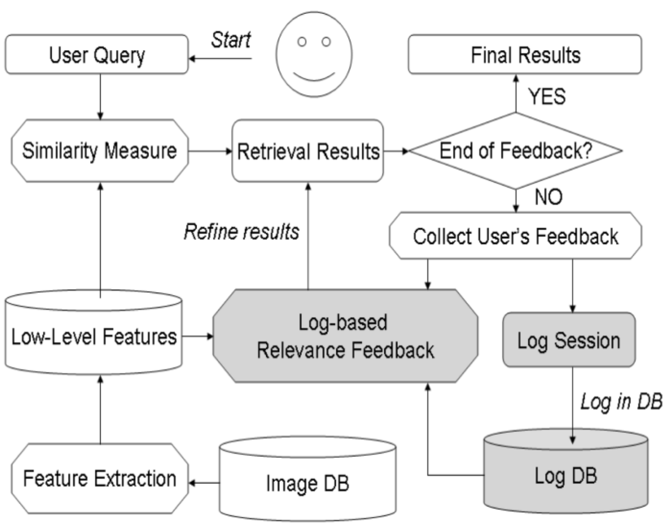

Fig. 2.Architecture of Unified Log Based RF[6]

Support vector machine (SVM) algorithm, named Soft Label SVM, is use to make the learning algorithm more robust to erroneous log data in real-world applications to tackle the noisy data problem.

As shown in Figure 2, online relevance feedback from users is collected and stored in a log database. When feedback log data is unavailable, the log-based relevance feedback algorithm behaves exactly like a regular relevance feedback algorithm, which learns the correlation between low-level features and users information needs through the feedback image examples. When feedback log data is available, the algorithm will learn such a correlation using both the feedback log data and the online feedback from users. Thus, the log-based relevance feedback scheme is able to achieve the retrieval goal in only a few iterations with the help of the log data of user's feedback.

Aim of log-based relevance feedback problem for image retrieval is to look for a relevance function f_q that maps each image sample z_i to a real value of relevance degree within the range of 0 and 1,

$$f_q : Z \rightarrow [0,1]$$

based on the feature representation of images X, the log data of users feedback R, and the labeled images L acquired from online feedback. Both the low-level features of the image content, i.e., X, and the log data of users feedback, i.e, R, should be included to determine the relevance function $\boldsymbol{f_q}$.

Let $f_{R}(z_i)$ denote a relevance function based on the log data of user's feedback and $f_X(z_i)$ denote a relevance function based on the low level features of the image content. Both of them are normalized to [0,1] respectively. Then, the overall relevance function can be the combination of these two functions as follows:

$$f_q(z_i) = \tfrac{1}{2}(f_R(z_i) + f_X(z_i))$$

Advantages:

1. Unified Log based relevance feedback algorithm by Soft Label SVM (LRF-SLSVM) achieves a promising improvement even with a limited amount of log data.

2. The presence of noise in the log data is unavoidable when the data is collected from a real-world CBIR application. Unified Log based RF achieve better performance than the standard SVM algorithm in case of noise log data.

Issues:

1. Two main computational costs are inherited. One is the relevance computing of log data and the other is the training cost of Soft Label SVM.

2. It may be possible to learn the relevance function more effectively. In the current scheme, this technique only considers the classification model in the space of image features. It would be possible to apply the method in the reverse direction by first computing the soft labels from the image features and then building a classification model in the space of the users' relevance judgment.

3. The noise problem could be handled in other ways. For example, to alleviate the negative effect from noisy log data, we can modify the Soft Label SVM by enforcing an upper bound on the error terms in the optimization of the Soft Label SVM.

Generally comparison of different relevance feedback

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techniques is done in terms of its accuracy and its recall.
Accuracy= no. of retrieved relevant images/total retrieved images.

Recall= no. of retrieved relevant images/total no of images in the database.

Comparison Points		ULRF	RF
Normal amount of log data	Average Accuracy	0.65	0.5-0.53
	Average Recall	0.3	0.25
Small amount of log data	Average Accuracy	0.568	0.489
Small amount of noise in log data	Average Accuracy	0.635	0.535
Computational Cost		High	Less as compared to ULRF
Time Cost		8.09 secs	5.53 secs

Table.1 Comparison of Unified log based RF and general RF

B. *Feature-Adaptive Relevance Feedback (FA-RF)*

FA-RF[2] is a RF-based approach and uses two iterative techniques to make use of the relevance information: query refinement and feature re-weighting. Such technique uses the descriptions of both relevant and irrelevant image, as well as their number and proportions, to achieve adaptation across RF iterations. In CBIR, if the sample image is located near to the boundary of the relevant cluster in the feature space, the first retrieval may contain few relevant images. In this case, the query refinement mechanism is useful to move the query towards the middle of the cluster of relevant images. This method uses the sets of relevant and non-relevant images(D'_R and D'_N) specified by the user to calculate a new query by applying the Rocchio's formula:

$$Q' = \alpha Q + \beta \left(\frac{1}{N'_R} \sum_{i=1}^{N_R} F_i \right) - \gamma \left(\frac{1}{N'_N} \sum_{j=1}^{N_N} F_j \right)$$

Where Q is the previous query, N'_R, N'_N, are the numbers of images in D'_R, D'_N, and Fi, Fj are the feature vectors associated to the relevant and irrelevant images, respectively[10].

Availability of significant number of samples classified by the user as relevant and irrelevant makes it possible to associate a weight to the features, in order to indicate most important ones. In this technique, the query feature vector is set to the average of all relevant feature vectors.

This technique uses the concept of adaptive description of an image, by using the user's feedback to navigate in an extended feature space and to search for a highly matching subset of features. In the pre-processing phase, it extracts a large collection of parameters S from every image in the database, providing a very rich description of the relevant visual content. During the retrieval process, the system uses candidate subsets H_i of the set S, adaptively selected on the basis of the sequence of feedbacks received from the user. The subsets H_i are increasingly obtained by applying a set of rules.

Such rules are defined a priori, and aim of providing a more accurate description of the characteristics that are learned to be more discriminating according to user inputs. In practice, the feature space evolves as a finite-state machine (FSM).It is quite clear that the behavior of the system depends on both the selection of the first subset H_1 , and the definition of suitable replacement rules (i.e., the transitions of the FSM), which also depend on the characteristics of the set S . The current implementation is based on a coarse-to-fine adaptation, relying on a set of hierarchical replacement rules, according to the following procedure.

1) *Initialization:* It starts from a pre-defined unweighted subset H_1. Retrieves a first set of images based on the feature set H_1, collects the user feedback, and calculates the relative weights associated to the features in H_1.

2) *Feedback:* Then it retrieves a new set of images based on the weighted feature set computed at previous step, collect the user feedback and update the weights.

3) *Feature adaptation:* Then it computes a new subset according to the following replacement rules.

a) *Removal*: less discriminating parameters (weight below a lower threshold) are removed from the feature vector.

b) *Refinement*: Highly discriminating parameters (weight above a higher threshold) are replaced by a more detailed description (feature-dependent).

c) *Preservation*: Other parameters (weight between and) are left unchanged.

4) *Iteration:* Finally it calculates the weights for the new feature vector using the history (previous feedbacks) then go to step2.

The coarse-to-fine adaptation is achieved by applying the refinement rule (b) in step 3, thus achieving a better description of highly discriminating features. In general, the new features are not simply a finer version of the previous one (e.g., a better quantization of a given parameter), but instead an enriched source of information providing a stronger link between the image and the user perception of it.

The removal rule (a) is not strictly necessary, but allows keeping low the dimension of the subset, speeding up the computation. In step 4, the weights of the updated feature vector are automatically calculated based on the history, thus limiting the number of requested user's feedbacks. It has been observed that, when images retrieved and labeled in the initial feature space are used as training samples in the new feature space, they turn out to be more representative

Advantages:

1. This technique performs very well in terms of capability in identifying most important features and assigning them higher weights, as demonstrated by the comparison with classical feature-selection algorithms.

2. It shows a significant improvement of the retrieval accuracy in comparison with standard RF approaches.

Issues:

1. Feature replacement rules which are currently used in this technique are not optimized due to which it increases complexity and its cost.

Comparison Points	**FARF**	**RF**
Accuracy	64.06	49.48
Recall	68.33	52.78
Ability to identify important features	High	Less as compared to FARF

Table.2 Comparison of FA RF and general RF

C. Navigation Pattern Based Relevance Feedback (NPRF)

Navigation-Pattern-based Relevance Feedback (NPRF) [7] 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.

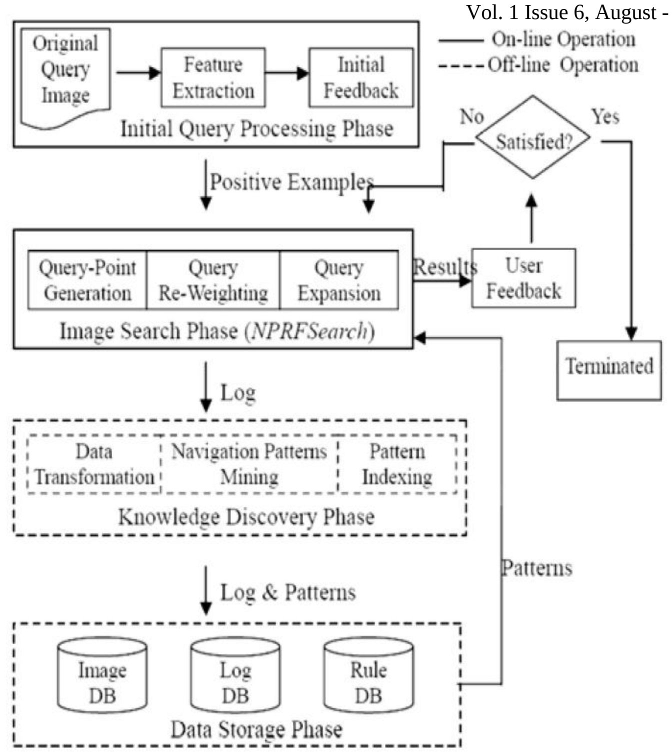

Fig. 3.Architecture of NPRF [7]

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

Online Image Retrieval

1) *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. Afterward, the good examples picked up by the user are further analyzed at the first feedback.

2) *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.

Offline Knowledge Discovery

1) *Knowledge Discovery Phase:* Learning from users 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.

2) *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 rule base 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 items on the transaction list. Navigation pattern mining stage focuses on the discovery of relations among the users browsing behaviors on RF. 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 itemsets). 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 {C1m| C1m ∈Q} where Q contains the set of starting query images related to different navigation trails, and several iteration 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.3 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, the sequential navigation pattern fC11→ C32 → C42} derived from frequent itemset {C11,C3,C42} when minimum support is 2.

Items	Count	Frequent e-itemset
C_{11}	2	Frequent-1 itemset
C_{12}	2	
C_{21}	3	
C_{32}	4	
C_{42}	3	
C_{11}, C_{32}	2	Frequent-2 itemset
C_{11}, C_{42}	2	
C_{12}, C_{21}	2	
C_{11}, C_{32},C_{42}	2	Frequent-3 itemset

Table.4 Example of Navigation Patterns

Advantages:

1. 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.

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 data sets, this technique would need parallel and distributed computing techniques which are also not yet included.

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Comparison Points	NPRF	RF(QPM and QEX)
No of user feedback	2	5-6
Average Accuracy	0.85	0.61-0.66
Average Recall	0.2	0.1-0.15
Time Cost	1.176 sec	5.5-6.5 sec

Table.5 Comparison of NPRF and RF

III. CONCLUSIONS

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

This paper has covered some of the recent and eminent relevance feedback techniques explaining their basic architectures, advantages and disadvantages. Much other related work exists, but the techniques mentioned here – Unified Log Based Feedback, FARF, NPRF are the prime ones and most efficient ones for the current implementation of relevance feedback in CBIR.

A unified log-based relevance feedback provides framework for integrating log data of user feedback with regular relevance feedback for image retrieval. FARF dynamically adapt not only the query parameters and feature weights but also the set of image descriptors (number and type) in order to better fit the user's perception. NPRF works by integrating the navigation pattern mining and a navigation-pattern-based search approach.

It is found that none of the existing approaches meets completely the requirements of an accurate CBIR system with relevance feedback because none of the techniques have completely solved the problem of semantic gap. So it is still undecided what the future truly holds for Improving and implementing Relevance Feedback in real world applications.

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