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# A two-level relevance feedback mechanism for image retrieval

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**Abstract**

Content-based image retrieval (CBIR) is a group of techniques that analyzes the visual features (such as color, shape, texture) of an example image or image subregion to find similar images in an image database. Relevance feedback is often used in a CBIR system to help users express their preference and improve query results.

Traditional relevance feedback relies on positive and negative examples to reformulate the query. Furthermore, if the system employs several visual features for a query, the weight of each feature is adjusted manually by the user or system predetermined and fixed by the system. In this paper we propose a new relevance feedback model suitable for medical image retrieval. The proposed method enables the user to rank the results in relevance order. According to the ranking, the system can automatically determine the importance ranking of features, and use this ranking to automatically adjust the weight of each feature. The experimental results show that the new relevance feedback mechanism outperforms previous relevance feedback models.


*Keywords:* Content-based image retrieval; Relevance feedback; Image database

## 1. Introduction

Image capture capabilities are evolving so rapidly that extreme amount of images is produced daily. The importance of digital image retrieval techniques increases in the emerging fields of publication on the Internet, digital library, medical imaging, etc. It is a hard work to retrieve a specific image from thousands of images by browsing one by one. Attaching text annotation to images and allowing a user to query images by matching text annotation may help the retrieval of a specific image; however, attaching text annotation to images by humans is expensive and time consuming.

Content-based image retrieval (CBIR) is a promising technology to assist image finding. CBIR retrieves images by visual features inherent in images. CBIR allows the user to query an image database by image examples, partial regions of an image, or sketch contours example, etc. IBM in 1995 developed the QBIC system (Flickner et al., 1995) that allows the user to query a large image database based on visual image features such as color percentages, color layout, and textures occurring in images. The user can match colors, textures and their positions without describing them in words. CBIR offers an alternative to retrieve desired images. CBIR is more convenient and economic than annotation-based image retrieval because the visual image features of all images in database can be automatically extracted.

In the past years, CBIR has been one of the most hot research topics in computer vision. The commercial QBIC

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(Bartell, Cottrell, & Belew, 1995) system is definitely the most well-known system. Another commercial system for content-based image and video retrieval is Virage (Hampapur et al., 1997), which has famous commercial customers such as CNN. In the academia, systems including Candid (Cannon & Hush, 1995), Photobook (Pentland, Picard, & Sclaro, 1996), and Netra (Ma, Deng, & Manjunath, 1997) use simple color and texture features to describe image content. The Blobworld system (Bartell et al., 1995) exploits higher-level information, such as segmented objects of images, for queries. A system that is available free of charge is the GNU Image Finding Tool (GIFT) (Rocchio, 1971). A few systems are available as demonstration versions on the Web such as Viper, WIPE or Compass.

Many studies show that relevance feedback can significantly improve the effectiveness of CBIR because relevance feedback helps the system to refine the feature's weight according to user's preference. Some users may want to find images with similar colors, whereas others may want to find images with similar shapes. Relevance feedback allows the user to reflect his preference to the system, then the system can reformulate the query according to the positive and/or negative examples responded by the user. In the Spink's Spink, Greisdorf, and Bateman (1998) study show that the degree of relevance will better identify the user needs and preferences.

The similarity consideration of a user is more complex than just like or dislike. The user can point out which results are actually more relevant than others. It means that the user can offer more precise information than just positive or negative examples. The similarity degree of human is gradual and fuzzy; it is not so trivial to be categorized into just relevance or irrelevance.

In this paper we propose a two-level relevance feedback mechanism that facilitates the user to determine the preferred images and assign a relevant degree to each image. Our system offers the user a flexible environment to feedback their opinions about the results retrieved by the system. The user can rank the preferred images to create a refined query for the system. Based on the ranked images the system can predict user's preference more precisely and achieve better performance.

The application of image retrieval to general image databases has experienced limitation in success, principally due to the difficulty of quantifying image similarity for unconstrained image classes (e.g., all images on the Internet). We expect that medical imaging will be an ideal application of CBIR, because of the more limited definition of image classes, and because the meaning and interpretation of medical images is better understood and characterized. In the experiment, the medical image data was applied to evaluate the proposed relevance feedback mechanism.

This paper is organized as follows. In Section 2, we review some related relevance feedback studies. The new relevance feedback mechanism is proposed in Section 3. In Section 4, we describe the image features that we use to represent the medical images. In Section 5, we use the CasImage dataset to evaluate our proposed methods. Section 6 presents conclusion and future works of this paper.

## 2. Related works

Relevance feedback is a supervised learning technique for improving the effectiveness of an information retrieval system (Rocchio, 1971). For a given query, the system first retrieves a list of ranked results according to a predefined similarity metrics. Then, the user selects a set of positive and negative examples from the ranked results, and the system reformulates the query and retrieves a new list, which is expected to match the user's query goal better than the original list. The main problem is how to incorporate positive and negative examples to refine the query and how to adjust the similarity measure according to the feedback.

The original relevance feedback method, in which the vector model (Buckley & Salton, 1995; Rui & Huang, 1999) is used for document retrieval, can be illustrated by the Rocchio's formula (Rocchio, 1971) as

$$Q' = \alpha Q + \beta\left(\frac{1}{N_{R'}}\sum_{i\in D_{R'}} D_i\right) - \gamma\left(\frac{1}{N_{N'}}\sum_{i\in D_{N'}} D_i\right) \tag{1}$$

where $\alpha$, $\beta$ and $\gamma$ are suitable constants. $N_{R'}$ and $N_{N'}$ are the number of documents in $D_{R'}$ and $D_{N'}$, respectively. That is, for a given initial query $Q$, and a set of relevant documents $D_{R'}$ and non-relevant documents $D_{N'}$ responded by the user, the refined query, $Q'$, is moved toward positive examples and away from negative examples. This technique is also implemented in many content-based image retrieval systems (Ishikawa, Subramanya, & Faloutsos, 1998; Lu, Hu, Zhu, Zhang, & Yang, 2000). Experiments show that the retrieval performance can be improved considerably by using this approach.

Another method, the weighting method (Ishikawa et al., 1998; Rui & Huang, 1999), associates larger weights with more important vectors and smaller weights with less important ones. For example, (Rui & Huang, 1999) generalizes a relevance feedback framework based on low-level feature. An ideal query vector for each feature $i$ is described by the weighted sum of all positive feedback images as

$$q_i = \frac{\pi^T Y_i}{\sum_{j=1}^{n}\pi_j} \tag{2}$$

where $Y_i$ is the $n\times K_i$ ($K_i$ is the length of feature $i$) training sample matrix for the feature $i$ obtained by stacking the $n$ positive feedback training vectors into a matrix. The $n$ element vector $\pi = [\pi_1, \pi_2, \ldots, \pi_n]$ represents the degree of relevance of each of the n positive feedback images, which can be determined by the user at each feedback interaction. The system then uses $q_i$ as the optimal query to evaluate the relevance of images in the database. This strategy is widely used by many image retrieval and relevance feedback systems (Han & Kamber, 2001; Rui & Huang, 1999).

The Bayisian estimation method has been used in many probabilistic approaches to relevance feedback. Cox,