# Chapter 4 Relevance Feedback as New Tool for Computer-Aided Diagnosis in Image Databases

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# ABSTRACT

With the ever-growing volume of images used in medicine, the capability to retrieve relevant images from large databases is becoming increasingly important. Despite the recent progress made in the field, its applications in Computer-Aided Diagnosis (CAD) thus far have been limited by the ability to determine the intrinsic mapping between high-level user perception and the underlying low-level image features. Relevance Feedback (RFB) is a post-query process to refine the search by using positive and/or negative indications from the user about the relevance of retrieved images, which has been applied successfully in traditional text-retrieval systems for improving the results of a retrieval strategy. In this chapter, the authors review some recent advances in RFB technology, and discuss its expanding role in content-based image retrieval from medical archives. They provide working examples, based on their experience, for developing machine-learning methods for RFB in mammography and highlight the potential opportunities in this field for CAD applications and clinical decision-making.

# INTRODUCTION

With the growing volume of images used in medicine, the capability to retrieve relevant images from large databases is becoming increasingly important (Bimbo, 1999; Rui & Huang, 1999). The key to a successful image retrieval system lies in the development of appropriate similarity metrics for ranking the relevance of images in a database to the query image. Content-Based Image Retrieval (CBIR) has been proposed to overcome the difficulties encountered in textual annotation for large image databases. Relevance Feedback (RFB) is a post-query process to refine the search by using positive and/or negative indications from the user of the relevance of retrieved images. It has been applied successfully in traditional text-retrieval systems for improving the results of a retrieval strategy (Baeza-Yates & Ribeiro-Neto, 2011; Chowdhury, 2010; El-Naqa, Yang, Galatsanos, & Wernick, 2002).

Despite the progress made in the general area of image retrieval in recent years, its success in biomedicine has been quite limited until recently, where significant evolution has taken place (El Naqa, Wei, & Yang, 2010; Muller, Michoux, Bandon, & Geissbuhler, 2004; Shapiro, et al., 2008; Wong, 1998). In our previous work, we investigated the use of CBIR for digital mammograms (El Naga, Yang, Galatsanos, Nishikawa, & Wernick, 2004; El-Naga, et al., 2002). The goal was to provide the radiologist with a set of images from past cases that are relevant to the one being evaluated, along with the known pathology of these cases. We conjecture that by presenting images with known pathology that are "visually similar" to the image being evaluated, a mammogram retrieval system may serve as a more intuitive aid to radiologists, potentially leading to improvement in their diagnostic accuracy. Furthermore, it is expected that such a technique would be a useful aid in the training of students and residents, since it would allow them to view images of lesions that appear similar, but may have differing pathology.

In this chapter, we review some recent advances in RFB technology, and discuss its expanding role in CBIR from biomedical archives. We provide working examples based on our experience in applying different RFB strategies in mammography with a special focus on developing machinelearning methods to improve effectiveness and efficiency of CBIR for mammography. Finally, we highlight the current challenges and the potential opportunities in this field for CAD applications and computerized clinical decision-making.

### BACKGROUND

# Relevance Feedback in Content-Based Image Retrieval

Relevance Feedback (RFB) has been an active area of research in the CBIR community since it was introduced in the 1990s, of which the goal is to resolve ambiguities in retrieving images through user interaction (Kurita & Kato, 1993; Rui, Huang, Ortega, & Mehrotra, 1998). A fundamental difference between relevance feedback in image retrieval and document retrieval is that the latter is based on a fixed symbolic representation, which has a clear mapping to human interpretation, while for images there is a lack of such a clear mapping between high-level user perception and low-level image features (e.g., color, texture, shape, etc.). Unlike text documents, an image database cannot adopt a net clustering structure, and the number of classes and the class membership in the database are not readily defined beforehand, because they can be user-dependent and time varying (Zhou & Huang, 2003). Nonetheless, it has been demonstrated that RFB techniques could boost the retrieval effectiveness. There are some key issues that need to be addressed in developing a successful RFB system, e.g., (1) the number of labeled feedback samples is usually small; and (2) real-time computation is a necessary practical requirement. Recently, there have been different methods proposed to address these issues. A rather comprehensive review of RFB techniques in image retrieval can be found in (Zhou & Huang, 2003). Below we review some of the recent efforts in RFB within the scope of this chapter.

Cox *et al.* developed a Bayesian framework to model the user behavior given a query image (Cox, Miller, Minka, Papathomas, & Yianilos, 2000), where the objective is to minimize the expected number of future search iterations using an entropy estimate. Tong and Chang proposed a support vector machine (SVM) binary classifier to separate relevant from irrelevant images using an 19 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage: www.igi-global.com/chapter/relevance-feedback-new-tool-computer/62225

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