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PRoSPer: Perceptual similarity queries in medical CBIR systems through user profiles ☆

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In this paper, we present a novel approach to perform similarity queries over medical images, maintaining the semantics of a given query posted by the user. Content-based image retrieval systems relying on relevance feedback techniques usually request the users to label relevant/irrelevant images. Thus, we present a highly effective strategy to survey user profiles, taking advantage of such labeling to implicitly gather the user perceptual similarity. The profiles maintain the settings desired for each user, allowing tuning of the similarity assessment, which encompasses the dynamic change of the distance function employed through an interactive process. Experiments on medical images show that the method is effective and can improve the decision making process during analysis.

1. Introduction

Due to the huge amount of digital images daily generated in hospitals and medical centers, these images are a true asset for the decision making process during diagnosing and medical training. The analysis of such volume of images is almost impossible to be manually done, since it is extremely time consuming and wearisome.

Methods aimed at developing effective Content-Based Image Retrieval (CBIR) systems for medical images have been attracting particular attention from researches. Despite the recent research efforts, CBIR remains a challenging task, mostly due to the phenomenon known as “semantic gap”, where the low-level features automatically extracted from images do not satisfactorily represent the semantic interpretation of the images in terms of the users' perception [2]. Furthermore, usually the choice of the distance function for computing the similarity is usually ad hoc, what may worsen the result quality.

The human similarity evaluation is inherently complex, as it is highly subjective and dependent on the user intent. It is common that a medical image presents several clinical findings with distinct visual patterns. Different specialists may be interested in different clinical findings, therefore employing distinct similarity criteria. For instance, in Computed Tomography (CT) lung exams, different types of pulmonary lesions require different analysis procedures from the radiologist. Usually, changes in lesions are hard to identify, requiring more training by the radiologists, in order to correctly classify them [3]. The same problem is also verified regarding mammogram exams and in almost all medical specialties. Moreover, there is no general distance function capable to capture the user's perception, even when restricted to a given type of feature or image domain. Thus, it is fundamental to define techniques to identify the best distance for every type of feature according to the user intention.

One alternative to enhance the retrieval accuracy of a query is to collect information related to the user perceptual similarity during the searching process. Such data can be employed to compose the user profile, which describes how each user understands similarity in his/her specific context. User profiles compose a knowledge base that can provide clues to enhance the similarity evaluation and can also support training. For example, resident physicians could benefit from the profiles collected from specialists in the field to improve their learning process, once they would see what was the perception of a senior specialist.

In this paper, we propose the *PRoSPer* (**P**e**R**ceptual **S**imilarity Queries through User **P**rofiles) framework, which applies an effective strategy to survey the user' profiles and employs them to tune the similarity evaluation, identifying the distance functions that best approximate the users' perception. The proposed framework interactively captures the user's intention according to the similarity between medical images during the relevance feedback

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process [4], in order to assist the specialist to retrieve images that best meet his/her expectation. Our framework can be seamlessly integrated to a CBIR process, enhancing the image retrieval effectiveness with a minimum user effort.

The remainder of this paper is structured as follows. Section 2 presents the background needed to follow our methodology. Section 3 details the proposed framework. Section 4 introduces the image datasets used to evaluate the framework. Section 5 shows experimental measurements and discusses the experiments. Section 6 analyzes the achieved results. Finally, Section 7 presents the conclusions of the work.

2. Background

The success of a CBIR system is directly related to its capacity of adequately measuring the similarity between images. This section introduces how to evaluate the similarity between pairs of images as well as techniques to enhance this process through user feedback and profiling.

2.1. Content-based image similarity evaluation

Digital images are represented as a matrix of pixels, which does not evidence the semantics of the pictured scene/object. To better exploit semantics, the images are usually processed using algorithms, called feature extractors, that produce feature vectors describing the image visual patterns mostly regarding color, texture and shape. The similarity evaluation of the images is performed comparing their feature vectors using a distance – or dissimilarity – function to quantify how close (or similar) each pair of vectors is.

Concerning medical images, one of the most common technique used to represent an image regarding its gray-level (color) distribution is the traditional histogram. It is a simple feature extractor, which describes the probability of a given image pixel to have a specific gray-level by counting its frequency of occurrence [5]. Texture features are widely employed to discriminate tissues in medical images. For instance, the Haralick descriptors [7,6], based on second-order statistics and obtained from co-occurrence matrix, have been largely used to a texture-based image representation [8].

Shape features are useful to capture the shape of regions in medical images. An example of shape feature extractor is based on the Zernike moments, which are a combination among the Zernike polynomials formulation and the general moments theory, generating a set of orthogonal moments [9].

Several distance functions are used for CBIR. The most common ones are those from the Minkowski family (also known as the L_p distance functions) [10], although other distances such as Canberra have produced promising results in similarity search [11]. Setting up the best distance function to each kind of image feature extractor is not a trivial task. It has been shown that there is an appropriate relationship between the intrinsic features extracted from complex data and the distance function employed that improve the quality of the similarity evaluation [11]. Moreover, it has been noticed that this relationship depends on the user intention and on his/her notion of similarity, thus it should rely on user feedback.

2.2. Relevance feedback in CBIR

A strategy employed in CBIR systems to obtain a better approximation of the user's expectations and preferences is the Relevance Feedback (RF). Relevance feedback allows the user to weigh the returned answers, informing which images are relevant according to a given image query [4]. Thus, RF is a real-time learning strategy that adapts the answer from a retrieval system exploring the user interaction.

Basically, considering the CBIR process a relevance feedback technique is composed of three steps. In the first step, the system retrieves the most similar images according to the initial query. During the second step, the users guide the search process, weighing the returned images based on a relevance degree (e.g. relevant or irrelevant). In the third step, the system captures the user's expectation based on the performed feedback and automatically adjusts the further queries based on the user's informed relevance. The second and third steps are repeated until the user is satisfied with the results. As the system captures the user's intention when a new query is performed, the resulting set of images can be continually improved until the gain flattens, according to the iterative learning process [12].

Regarding the second step of the RF technique, several algorithms with different approaches have been proposed so far [14,13]. There is also a number of techniques that can be employed in the third step. According to the strategy employed, these techniques can be divided into two main categories: query point movement, and re-weighting schemes of the similarity measure. The query point movement techniques consider that a query is represented by a single query center. Therefore, at each user interaction cycle, the strategy estimates an ideal query center in the query space, moving the query center towards the relevant examples and away from the irrelevant ones. On the other hand, the re-weighting techniques usually focus on adjusting weights to each dimension of the feature vector emphasizing some dimensions and diminishing the influence of others. For an extensive description and comparison of several methods of relevance feedback see [15].

Several relevance feedback strategies have been applied to CBIR aiming at reducing the "semantic gap". However, current RF techniques in the great majority of CBIR systems do not present a satisfactory user interaction. The main reason is that the user's perception is not properly captured and maintained by the system. All the information acquired during the RF is lost when the user finalizes the interaction with the system. On the contrary, in the present paper, we take advantage of the images labeling to capture the user's intention and store the information implicitly provided by the user for further improving the searching process, as we will show in Section 3.

2.3. User profiles in data retrieval

A user profile can be seen as a collection of personal information (i.e. a user model). Thus, the profiles can be employed by a system to exploit the user preferences. User profiles are commonly used by search engines to provide recommendations about the user preferences, as is done, e.g. in collaborative filtering [16] and techniques that organize users with similar interest. Considering the medical field, the concept of user profiles can be employed to capture and maintain the semantics of a given specialist in an image domain.

The first phase for a user's profiling survey collects preliminary information about the user. It can be divided into two main categories: static and dynamic profiling.

Static profiling aims at analyzing information that usually comes from users themselves through survey forms (e.g. interviews and questionnaires) or electronic registration. It is employed to capture the general interests of the user. For instance, information such as the user image domain (e.g. lung CT images, head MRI images, among others), the user expertise degree (e.g. senior specialist, resident physician). However, this profiling strategy presents some drawbacks. Its static nature implies that it is valid during a certain