Image Retrieval in Medical Applications The IRMA-Approach

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1 Introduction

The importance of digital image retrieval techniques increases in the emerging fields of medical imaging and picture archiving and communication systems (PACS). Up to now, textual index entries are mandatory to retrieve medical images from hospital archives or other sources [1]. This also holds for digital archives in DICOM-format [2]. In contrast, information contained in medical images differs considerably from that residing in alphanumeric format [3].

Common systems for content-based image retrieval (CBIR) [4] have low data-entry costs and, consequently, only a rudimentary understanding of image content. Such systems make no distinction between important and unimportant features or between multiple objects in the image. The features used for automated indexing characterize the entire image rather than unique regions or objects. In contrast, queries of medical or diagnostic relevance include searching for organs, their relative locations, and other distinct features such as morphological appearances. Therefore, common CBIR-systems cannot guarantee a meaningful query completion when used within the medical context [5]. Therefore, the results are rather poor when common CBIR-systems are used to retrieve medical images [6,7].

TAGARE et al. point out some of the unique challenges confronting retrieval engines with medical image collections [3]. Medical knowledge arises from anatomic *and* physiologic information, which quite often is obtained by the radiologist simultaneously during the diagnostic process. Hence, regional features are required to support diagnostic queries. However, interpretation of medical images is dependent on both, image and query context. Since the context of queries is unknown when images are entered into the database, the database scheme must be generic and flexible. Particularly, the number and kind of features extracted from the image are subject to continuous evolution. Furthermore, medical image interpretation is a complex and poorly understood process. Diagnostic inferences derived from images rest on an incomplete, continuously evolving model of normality. Hence, categorization and registration of medical images is required to support diagnostic queries on a high level of image interpretation.

2 The IRMA-Approach

Image retrieval in medical applications (IRMA) requires a system suitable for primitive and semantic queries as well as browsing without restrictions on either image category or query content. In the following, we present the IRMA-approach for medical CBIR-systems [8]. To enable complex content understanding the IRMA-concept is based on a conceptual and algorithmic separation of seven processing steps (Fig. 1):

- categorization with respect to image modality, anatomic region, function system, and body orientation using global image features
- registration in geometry and contrast for each likely category
- feature extraction using local features
- feature selection and combination with respect to category and query content
- indexing resulting in a hierarchical multi-scale blob representation
- identification of blobs by linking a-priori knowledge to image content
- retrieval processed on the abstract blob-level

The processing steps correspond to five semantic layers for knowledge representation. Likewise other systems, the unprocessed images form the *raw data layer*. Categorization and registration within each category are the first level where medical knowledge is incorporated into the IRMA-system. Hence, both steps result in the *registered data layer*. While other medical CBIR-systems are restricted to a certain modality or diagnostic procedure [9,10,11], the registered data layer in IRMA allows queries across all kind of medical images regardless of modality, region, or orientation. The *feature layer* is the third level of knowledge-based image processing. The separation of local feature extraction and feature selection is the major advantage in comparison with other systems. This separation makes the feature layer query dependent. Note that in contrast to other authors, spatial relationship characteristics are not modeled in the feature layer [9]. The fourth layer is obtained from indexing. We use the nomenclature introduced by CHU et al. and call it the *scheme layer* [9]. In the scheme layer, blob-structures represent the entities and the spatial relationships among them. The modeling of spatial relationships is emphasized by the hierarchical blob-concept. Hierarchies not only provide an efficient way to focus on regions of interest but also enable the introduction of query-specific knowledge to the processing. The *object layer* contains detailed knowledge on image content and hence, it is also referred to as knowledge layer [9].

3 Discussion

TAGARE et al. postulate the necessity of several tools for retrieval in medical imaging databases: non-textual indexing, customized scheme, dynamic modules, similarity modules, comparison modules, iconic queries, descriptive language, multi-modality registration, image manipulation [3]. Although all CBIR-systems provide non-textual indexing, the IRMA-approach is specially designed to handle primitive and semantic queries as well as browsing of medical images with respect to medical applications. Hierarchical blob-structures are build from selected local features. However, new

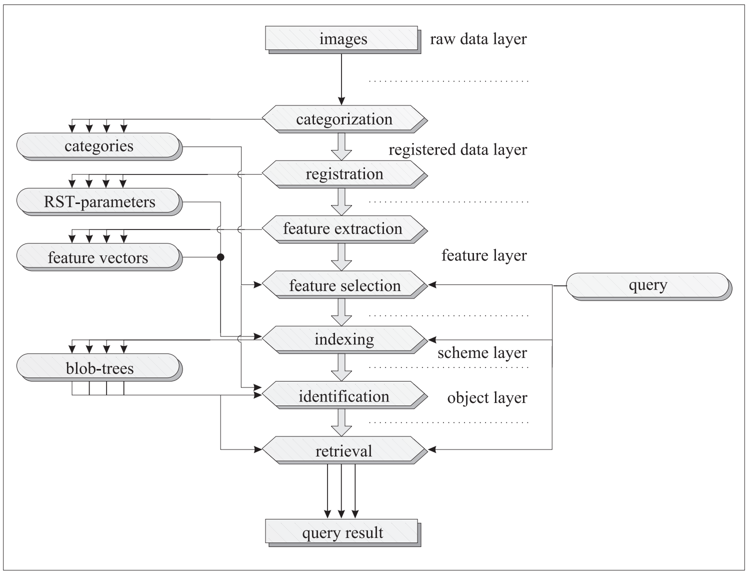

Fig. 1. Processing modules and semantic layers of the IRMA-system

feature extraction methods can be added at any time to the IRMA-system. The IRMA-system provides a development platform in which deamons automatically poll job lists from distributed systems and recreate all necessary database entries by parallel processing [12]. Note that this equals the customized and dynamic scheme in the sense of TAGARE et al. We also agree with the authors that similarity and comparison modules must be available within the descriptive language. Those concepts fit the IRMA-approach although they have not been implemented yet. Iconic queries cover image examples, sketches or prototypes. They are directly supported within IRMA by the incorporated QBE-concept. Because prototypes are part of the IRMA-system, their importance is even more emphasized by the IRMA-approach when compared to the approach by TAGARE et al. This also holds for registration. In IRMA, registration of images is performed automatically while TAGARE et al. only suggest to provide interactive tools for registration and image manipulation.

In general, the IRMA-concept is related to the Blobworld-project [12]. However, there are several important extensions of the Blobworld-concept especially designed for medical purposes:

– Each of the processing steps uses a more conceptional formulation of a-priori knowledge and it hierarchically regards details from global to local image properties.
– Medical images are categorized to enable content-based processing.
– Each image belongs to several categories with different probabilities.
– Several blob representations are generated since several sets of feature images exist for each category. The selection depends on both query and image content.
– Each blob-representation is hierarchically ordered on different resolutions (multi-scale) supporting queries on entire images and regions of interest.

– The blob-representations are registered to a prototype. This enables efficient image comparison on blob-level as well as easy identification of image structures.

By these extensions, a-priori knowledge on both image and query content is adjunct to content-based image indexing. Therefore, the IRMA-concept provides a high amount of content understanding and enables highly differentiated queries on an abstract information level. Furthermore, the IRMA-concept fulfills the demands for medical image retrieval systems postulated by TAGARE et al. and therefore, IRMA promises satisfactory query completion [3].

In first practical experiments, the categorization step was evaluated on 1,617 images of six classes taken from daily routine. The best classification error rate of 8.0% was achieved using invariant distance measures within a statistical framework, which means a relative improvement of 42% with respect to the baseline statistical system with 14.0% error rate and a relative improvement of 56% with respect to the Euclidean distance nearest neighbor error rate of 18.1% [13].

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