A MONOHIERARCHICAL MULTIAXIAL CLASSIFICATION CODE FOR MEDICAL IMAGES IN CONTENT-BASED RETRIEVAL

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ABSTRACT

Large efforts have been made for general applications of content-based image retrieval (CBIR). Established CBIR-systems globally evaluate color, texture, and also shape for retrieval. In medical imaging, local image characteristics are fundamental for image interpretation, which is based on a large amount of a-priori knowledge. Therefore, CBIR is rather seldom applied to medical images. Successful approaches strongly focus on a certain imaging modality and restrict queries to a well-defined diagnostic background. With respect to a general image retrieval in medical applications (IRMA), the system needs to determine the kind of image dealing with at a very early stage of processing to enable knowledge modeling required in further processing steps. In particular,

1. the imaging modality including technical parameters,
2. the orientation of the image with respect to the body,
3. the body region examined, and
4. the biological system under evaluation

must be determined in order to select appropriate local techniques for image analysis. These four aspects build the axes of a general classification code for medical images. All axes are monohierarchically structured into three or five levels. The code is applied within the IRMA-project for medical image retrieval but also applicable for a great variety of applications in medical imaging in general.

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 external sources [1]. This also holds for digital archives in DICOM-format [2]. In contrast, information contained in medical images differ considerably from that residing in alphanumeric format [3]. Common systems for content-based image retrieval (CBIR) have low data-entry costs and, consequently, only a rudimentary understanding of image content [4]. 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]. Consequently, the results are rather poor when common CBIR-systems are used to retrieve medical images [6, 7].

Recently, a number of medical image retrieval systems have been introduced. For instance, the ASSERT-system analyses CT images of the lung with respect to eight certain diagnostic inquiries [8], KMeD and COBRA retrieve ventricular shapes extracted from MR images of the head [9, 10], I-Browse operates on histological slices [11], and the system of Zhang et al. assists dentists to determe bone destruction in intra-oral radiographs [12]. Resulting from manual components during indexing, the data-entry costs of some of these systems are rather high. In addition, all approaches are focussed on a special diagnostic context restricted to a certain modality.

Tagare et al. have pointed out some of the unique challenges confronting retrieval engines with general collections of medical images [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. Furthermore, interpretation of medical images is dependent on both, image and query con-

*The IRMA-project has been founded by the German Research Community (DFG, grant Le 1108/4-1), http://irma-project.org.

text. Since the context of queries is unknown when images are entered into the database, the database scheme must be generic and flexible. The number and characteristics 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. In this paper, we introduce a classification code for categorization of medical images, which is fundamental for image retrieval in medical applications (IRMA).

2. THE IRMA-APPROACH

A general CBIR-approach must allow primitive and semantic queries as well as browsing without restrictions on either image category or query content. In the following, we briefly summarize the IRMA-system for medical CBIR [9]. To enable complex content understanding, the IRMA-concept is based on a conceptual and algorithmic separation of seven processing steps (Fig. 1):

1. categorization using global features,
2. determination of parameters for registration in geometry and contrast for each likely category,
3. feature extraction using local features,
4. feature selection and combination with respect to category and query content,
5. indexing resulting in a hierarchical multi-scale blob representation and registration,
6. identification of blobs by linking a-priori knowledge to image content,
7. 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. 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 [13]. The fourth layer is obtained from indexing. We use the nomenclature introduced by Chu et al. and call it the scheme layer [13]. 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 into the processing. The object layer contains detailed knowledge on image content and hence, it is also referred to as knowledge layer [13].

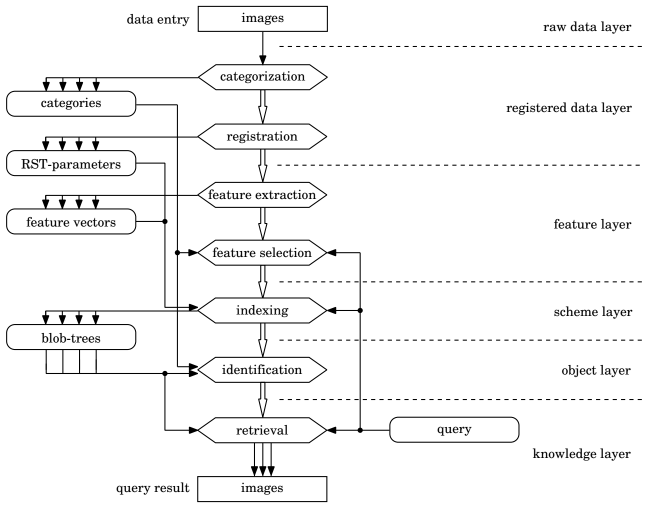


Fig. 1. IRMA represents the knowledge of a medical expert on different levels of abstraction, which also describe the flow of computation. (RST – rotation, scale, translation)

3. CODE FOR IMAGE CATEGORIZATION

Within the IRMA-system, categorization is the first of seven successive processing steps. A four-axis coding system has been developed for categorization of medical images in general:

T: image modality (technical),

D: body orientation (directional),

A: body region examined (anatomical),

B: biological system (biological).

All parts have their own complete settings. In other words, the code-axes are orthogonal and each axis is built monohierarchically. The technical code differentiates physical methods and their subtechniques, which have major impact on the structural appearance of imaged organs or tissue and hence, also on proper algorithms for local image interpretation. The orientational code assesses the positioning of the patient with respect to the imaging modality. The anatomical code systematically describes the entire human body with respect to location, while the biological code covers the biological system imaged. A complete IRMA-code is denoted sequentially separating the axes by hyphens, i.e. T–D–A–B. Within each axes, the alphanumeric coding is used for each digit, i.e. [0..1,a..z], where 0 denotes "no further specification".

3.1. Technical Code

The IRMA-code describes within a maximum of four positions the technical method. It starts up with the imaging physical technique (e.g.: 1 x-ray, 2 ultrasound, 3 magnetic resonance, 4 optical, ...) showing in more detail the modality-position (e.g.: 11 plain film projection radiography, 12 fluoroscopy, 13 angiography, 14 computed tomography, ...). A third digit specifies the technique (e.g.: 111 digital, 112 analog, 113 stereometry, 114 stereography, ...) and the fourth position of T-code assesses subtechniques (e.g.: 1111 tomography, 1112 high energy, 1113 low energy, 1114 parallel beam, ...) External ads like contrast media application, drugs and additional markers are coded by the fifth position while an optional sixed digit might be added to determine technical modulators such as micro-focus or magnetic resonance coils. However, this is not done within the IRMA-system.

3.2. Directional Code

This three-digit part of the IRMA-code incorporates a two-step orientation description starting with the common orientation (e.g.: 1 coronal, 2 sagital, 3 transversal, 4 other) and giving more a detailed specification in the second position (e.g.: 11 posterior-anterior (pa), 12 anterior-posterior (ap)). Note that it is important to distinguish pa- and ap-direction since organs and bone structures might differ in scale, for instance, supposing plain x-ray chest imaging. Independent from the relative orientation of body region and imaging system, functional onrientation tasks of the examination can also be described (e.g.: 111 standing, 112 lying, 113 inclination, 114 reclination ...).

3.3. Anatomical Code

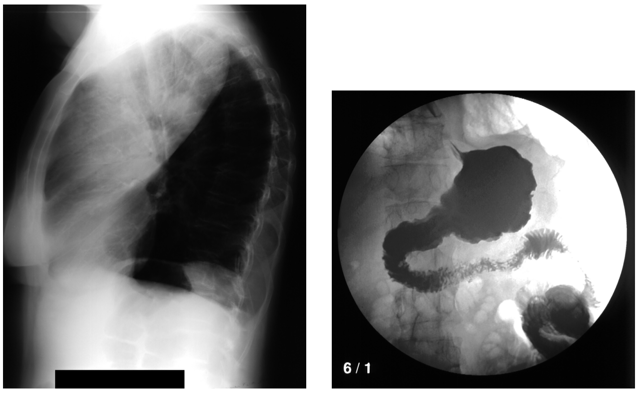
The IRMA-Code supports complete coding of the anatomical region. In total, nine major regions are defined (e.g.: 1 total body, head/scull, 3 spine, 4 upper extremity, ...) with up to three positions within the code (e.g.: 3 spine, 31 cervical spine, 311 dens).

3.4. Biological Code

Beside the body part examined, it is important to determine the organ system that is imaged. For example, flouroscopy of the abdominal region may access the cardiovascular or the gastrointestinal system. On the top-level of the functional IRMA-code, ten organ systems are specified (e.g.: 1 cerebrospinal system, 2 cardiovascular system, 3 respiratory system, 4 gastrointestinal system ...) each of which having up to three digits to exactly identify the organ in question (e.g.: 1 cerebrospinal system, 11 central nervous system, 111 metencephalon).

4. EXAMPLES

Figure 2 gives two examples of image classification using the IRMA-code. The image on the left is coded: x-ray, projection radiography, analog, high energy, no contrast agent – sagittal, left lateral decubitus, inspiration – respiratory sytem, lung – chest. The image on the right is coded: x-ray, fluoroscopy, analog, low energy, liquid contrast agent – coronad, ap, supine – abdomen, upper abdomen, middle – gastrointestinal system – stomach.



IRMA: 11223–211–3f0–500   IRMA: 12235–128–712–430

Fig. 2. IRMA-coded thorax and abdomen radiographs.

5. DISCUSSION

Currently, a database is assembled to host about 10,000 images from daily routine. Up to now, 6,000 images have been classified with the complete code. It was shown that the code is sufficient to describe more than 99% of the X-ray images completely. Due to the tree structure of the code, extensions are possible and will be introduced when new imaging modalities or technical properties show up, resulting in modified appearances of diagnostic images.

While other medical CBIR-systems are restricted to a certain modality or diagnostic procedure [8 – 13], the registered data layer in IRMA allows queries across all kinds of medical images regardless of modality and orientation as well as the anatomical region or biological system imaged. In a very first step of processing, categorization within the IRMA system is performed by global feature analysis.

These features include gray scale, texture, structure, shape as well as statistical and frequency domain properties resulting in a single feature vector representing the entire image.

All images are manually classified by radiologists according to the four-axes IRMA-code to allow supervised optimization of the IRMA categorization step. In first practical experiments, the automatic categorization was evaluated on 1,617 images of six classes. 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% [14]. Since all further IRMA processing steps are performed on several likely category hypotheses (Fig. 1), this error rate is quite sufficient.

In general, the IRMA-concept is related to the Blobworld-project [15]. However, there are several important extensions of the Blobworld-concept especially designed for medical purposes, which are based on the monohierarchical multiaxial classification code for medical images introduced in this paper. For instance, 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 and registered to a prototype that is also established by means of the IRMA-code.

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].

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