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Pattern Similarity of Medical Images for Texture Based Data Base Retrieval and Data Mining

P.K. Kumaresan[1], R.M. Suresh[2], R. Sivasubramaniam[3] and A. Nagappan[4]

[1]*Professor, Information Technology,*
V.M.K.V. Engg. College, Vinayaka Missions Univerisity, Salem, India
E-mail: kums_slm@yahoo.com
[2]*Professor & Vice Principal, R.M.D. Engineering College,*
Kavaraipettai, Thiruvallur Dt., India. E-mail: rmsuresh@hotmail.com
[3]*Professor, Information Technology, Institute of Road Transport Technology,*
Erode, India. E-mail: rss_1232@yahoo.com
[4]*Professor & Principal, V.M.K.V. Engg. College,*
Vinayaka Missions University, Salem, India. E-mail: nags_slm@yahoo.com

Abstract

A novel scheme for efficient content based medical image retrieval, formalized according to the PANDA (Patterns for Next generation Database systems) framework. The proposed scheme involves low-level feature extraction from image regions followed by clustering of the feature space to form higher-level patterns. The component of each pattern include a cluster representation and a measure of quality of the image content representation achieved by the pattern. The similarity between two patterns are estimated as a function of the similarity between both structure and the measured components of the patterns. Indexing of digital imagesand querying techniques have extensively been studied and few systems are dedicated to medical images today however the need for content based analysis and retrieval tools increases with the growth of digital medical image databases and data mining. Analyzing the medical image properties and evaluated the Gabor - filter based features extraction for medical images indexing and classification. The goal is to perform clinically relevant queries on large image databases that do not require user supervision. After the demonstration on the concrete case of human imaging that these techniques can be used for indexing, retrieval by similarity queries, and to some extent, extracting clinically relevant information out of the images.

Keywords: Content based image retrieval (CBIR); Data Mining; Patterns for Next generation Database systems (PANDA); Medical imaging; Image categorization.

Introduction

One of the primary tools used by physicians is the comparison of previous and current medical images associated with pathologic conditions of texture based. As the amount of pictorial information stored in both local and public medical databases is steadily growing due to high resolution imaging and technological advancements, efficient image indexing and retrieval is a necessity. Medical images are a key investigation tool for medical diagnosis and pathology follow-ups. Digital imaging is becoming the standard for all image acquisition devices and, there is an increasing need for data storage and retrieval. Medical images represent an enormous amount of data: the annual production of a single average size radiology department represents tens of terabytes of data. Therefore, petabytes of medical images are produced in industrialized countries each year. In the last decade the advances in information technology allowed the development of Content-Based Image Retrieval (CBIR) systems, capable of retrieving images based on their similarity with one or more query images. Some of these systems are QBIC [1], VisualSEEK [2], Virage [3], Netra [4], PicSOM [5], SIMPLicity [6], CIRES [7], and FIRE [8].

More than fifty CBIR systems are surveyed in [9]. With the growth of medical databases, new applications devoted to statistical analysis of medical data such as breast cancer screening, lung images analysis, oncology etc are commonly used. The datasets used in these applications are not images of one patient or a collection from one radiology department but rather images showing a particular pathology or specific features. This data set has to be dynamically assembled by automatically selected relevant images among available databases. The benefits emanating from the application of content- based approaches to medical image retrieval range from clinical decision support to medical education and research [10].

These benefits motivated researchers either to apply general purpose CBIR systems to medical images [8] or to develop new ones explicitly oriented to specific medical domains. Specialized CBIR systems have been developed to support the retrieval of various kinds of medical images, including High Resolution Computed Tomographic (HRCT) images [11], breast cancer biopsy slides [12], Positron Emission Tomographic (PET) functional images [13], ultrasound images [14], endoscopic images [15], pathology images [16], spine radiographs [17], and mammographic images [18].

Content based image retrieval systems

Content-Based Image Retrieval (CBIR) emerged in the early 1990s mainly to index color photographs. In this approach, images are represented by a vector in a feature space and a similarity measure between images is defined from a dis tance in the feature space. Figure 1 presents the general architecture of CBIR systems proposed in [19]. Given a query image, such a system first extracts its feature vector and then compares it to those of the images stored in the database.

Many CBIR systems were developed during the last years, both by commercial firms and academia. The earliest and most famous one is QBIC (Query By Image Content) [1] which was proposed by IBM. Virage is another commercial CBIR which is for example used by CNN [20]. Many systems have also been proposed from the academia like Photobook [21], VisualSEEK [2], Mars (Multimedia Analysis and Retrieval System) [22] which proposes a solution of relevance feed back , Candid [23] or Netra [4]. All of those systems only use low level features (mainly color, texture and shape) and do not include any semantic level. Later systems like Blobworld [24] include a segmentation step in the query process to integrate higher level information. In Blobworld, the segmentation step is based on color, position and texture features and leads to a small number of homogeneous regions called blobs. Submitting a request, the user can select the relevant blobs he wants the query to be applied on.

Nevertheless, no system offers any interpretation of images yet, which would require a dedicated layer in the system. This loss of information from an image to its representation in a feature space is called the semantic gap [25]. There exists a large number of medical image acquisition devices among which computed tomography scanners (CT), magnetic resonance imagers (MRI), ultrasound probes (US) and nuclear imagers are the most widely used. They provide images with very different properties in terms of resolution, contrast, and signal to noise ratio. They are highly specialized and they produce images giving very different information on the human body anatomy and physiology.

Inside one modality, the tuning of an imager may lead to significantly varying images . As [26] notice, the medical image retrieval must often be processed according to pathology bearing regions which are precisely delimited on the images and could not be automatically detected in the general case. Moreover, low level features like color, texture or shape are not sufficient to describe medical images [19]. As a consequence, medical CBIRs require a high level of content understanding and interpretation of images, which implies their automatic segmentation [25]. Finally, a high level of query completion and accuracy is required by such systems to make them reliable from a clinical point of view [27].

Medical Images Indexing and Retrieval

Some specialized CBIR have thus been proposed in medical applications. Chu et al. [28] present an image retrieval sys- tem dedicated to brain MRI which indexes images mainly on the shape of the ventricular region. Korn et al [29] propose a system for fast and effective retrieval of tumor shapes in mammogram X-rays. Comaniciu et al [30] describe a system which aims at helping physicians in the diagnosis of lympho proliferative disorders of blood. Nevertheless, A description of the clinical use of such systems is very rare [25], except for the systems ASSERT [31], which is dedicated to HRCT images of the lung and includes information from physicians such as anatomical landmarks and pathology bearing regions and IRMA [32] which proposes a multi-step approach for the classification of images into anatomical areas, modalities and view points.

Research on improving the efficiency of the image retrieval process has mainly focused on image indexing techniques by utilizing data structures, such as R-trees [1,33], feature index trees [34], iconic index trees [31], and meshes of trees [35]. Other approaches to improving efficiency, include clustering of the image feature spaces [36,37], and utilization of alternative similarity measures, usually dependent on feature sets [38,39].

Motivated by these studies, a novel scheme for efficient content-based medical image retrieval that utilizes similarity measures defined over higher-level *patterns* associated with clusters of low-level image feature spaces is proposed in this research work. The term *pattern* is defined in the context of a state of the art framework named PANDA (PAtterns for Next generation Database systems) [40].

The PANDA framework

The Efficient management of patterns extracted from medical image databases is of vital importance due to the extremely huge storage requirements as well as the complexity of such kind of raw data. Taking advantage of the PANDA framework [41] we adopt the idea of a Pattern Based Management System (PBMS) as the infrastructure for managing patterns extracted from our CBIR scheme, in contrast to DataBase Management Systems (DBMS). The key concept of PANDA is that any type of pattern can be represented in a compact and unified way. This can be achieved through a Pattern-Base (PB) keeping information about extracted patterns. Such a PB introduced in [41] consists of three basic layers: the pattern, the pattern type and the class. A pattern type is a description of the pattern structure. A pattern is an instance of the corresponding pattern type and class is a collection of semantically related patterns of the same pattern type.

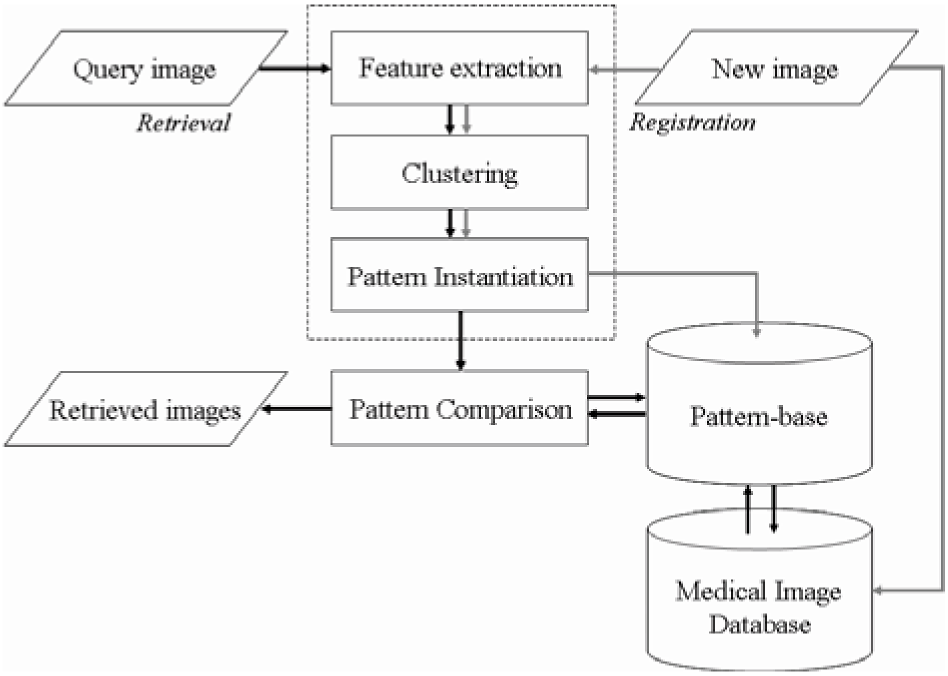

Fig. 1. General Architecture of CBIR methodology that embodies the proposed pattern similarity scheme. The black arrows indicate the data flow for image retrieval, whereas the grey arrows indicate the data flow for the registration of a new image.

The proposed content-based medical image retrieval scheme is outlined d in Fig. 1. It involves four steps: a) low- level feature extraction from each of the stored and query images, b) clustering of the extracted feature vectors per image, c) pattern instantiation of the clusters, and d computation of pattern similarities. The registration of a new image in the database involves the first three of the steps described for image retrieval (a, b, and c).

Localization and Segmentation

Local image features extraction in medical images gives different image information in areas covered by different tissues. In some medical applications where a tissue of interest covers a large fraction of the image or priori knowledge on the region of interest is available, extracting features by fixed blocs in the image is sufficient. However in the general case, one would like to identify features for each tissue in the image. This would require prior image segmentation. Medical image segmentation is one of the most challenging problem in medical image analysis and a very active research topic.

The feature vectors obtained were classified using the k- nearest neighbors algorithm [42]. An advantage of this method is that the only input parameter of the classifier is the number of classes. Each class is represented in the feature space by its barycenters that is initially randomly set. Then, each element is assigned to its nearest class (according to the Euclidean distance) and barycenters are iteratively updated. The algorithm stops when no more element moves from one class to another during an iteration.

Given that no assumption is done concerning the nature of the input data of the algorithm, it can be used for general purpose. Consequently, we tested this method on various images. Fig 2 shows the segmentation result on cardiac MRI segmented into three classes corresponding to the blood, the myocardium and the background (top row) and on brain MRI segmented into white matter, grey matter, cerebro-spinal fluid and skull (bottom row).

Segmentation assisted retrieval

Nevertheless, taking into account medical considerations, the retrieval of images that belong to the same instant that the query image is an important problem to cope with. Therefore, we focused on the retrieval of the end of systole into a 3D+t cardiac MRI sequence. To solve this problem, we propose the following method that includes the texture- based segmentation of the cardiac region we presented before. The fundamental hypothesis of the method lies in the fact that the contraction of the myocardium is correlated to the fineness of its texture: the more the myocardium will be contracted, the finer its texture will be. This hypothesis makes sense in an anatomical view because the contraction of the myocardium corresponds to a reduction of its volume and its fibers then lie more closely.

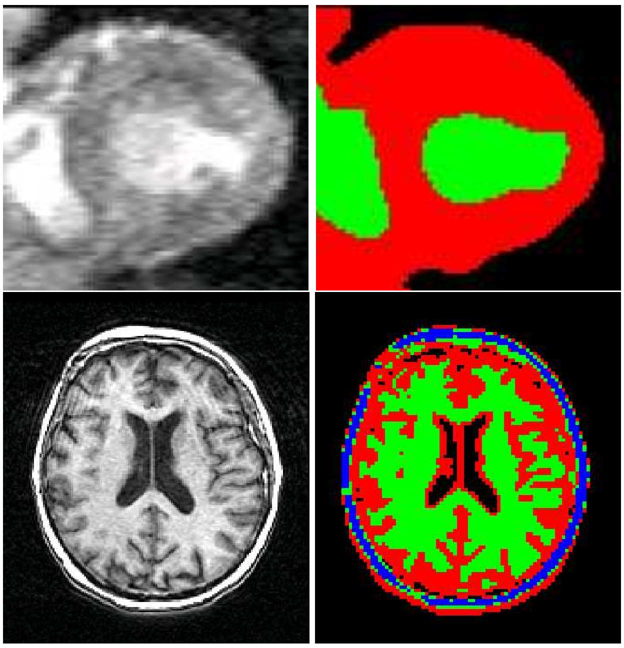

Fig 2: A cardiac(top) and a brain (bottom) MRI slice and the corresponding classified images

The principle of the queries is the computation of a distance between the features of the query image and those of the images in the database. Once all the distances are computed, the algorithm ranks the images of the database from the nearest to the furthest to the query image. We used Euclidean distance to process our queries. Thus, the distance between two feature vector f0 and f1 is given by the following formula:

$$d = \sqrt{\sum_{i=0}^{N} \left(f_O(i) - f_1(i)\right)^2}$$

where f0 (i) denotes the i^{th} coordinate of the vector f0 and N is the dimension of the feature space.

Result Evaluation

An indicative example retrieval of five radiographic images, based on the content of a query image is illustrated in Fig. 3. It can be noticed that the retrieved images contain semantically relevant regions (spine) although they belong to different categories. This could be justified if one considers that the proposed CBIR scheme involves features extracted locally from the images. Similar observations are valid for queries performed using radiographic images from other categories, and indicate that the patterns used for image representation carry substantial semantic information.

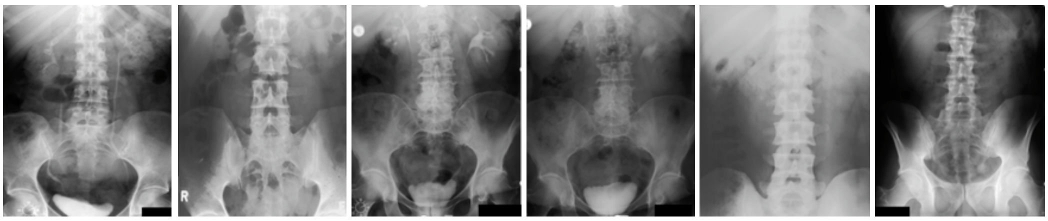

Fig. 3. Indicative example retrieval of radiographic images: (a) Query image (category: abdomen, uropoietic system), (b)-(d) Correct retrievals, (e)-(f) False retrievals (category: abdomen, gastrointestinal system).

Image retrieval system implementing the proposed scheme is highly associated with the feature set used for data representation. Selection of representative features, can lead to separable clusters. Provided that the clustering method chosen is compatible with the geometry of the feature space used, it is possible to minimize the performance divergence of the proposed and the conventional schemes.

By storing clustering patterns along with the low-level features set in a unified format further processing and analysis is facilitated. To date, most data mining algorithms have concentrated on the extraction of interesting rules directly from low-level data [43]. The approach proposed in this research work provides the means for deriving rules from the results of other data mining algorithms that is, mining from rules set. In the current work our initial low-level feature set is further processed and represented via clustering by higher-level patterns which are in a machine processible format. A significant advantage of this approach is that the nature of the rules to be extracted by this process contains different higher order semantics.

Image indexing and database clustering. To quantitatively evaluate the relevance of the feature vectors-based clustering of the database, we computed the mean and standard deviation of the vertical coordinate of the images in each cluster. Table 1 presents the values we obtained. The standard deviations are all inferior to 0.84 (their mean is 0.44), which indicates a relatively low dispersion among clusters. In clusters 4, 8 and 9, standard deviation is even null, which means that all the images of the concerned clusters have the same vertical coordinate in the initial sequences. Each of the other clusters contains an homogeneous set of images having close vertical coordinates in the initial sequences. This clustering result demonstrates the ability of our system to gather images of the database having the same vertical position in the initial sequences.

Discussion

In a preleminary level this work demonstrates the relevance of texture-based features for medical images indexing and retrieval. I has been analysed the properties of medical images. Global features are hardly usable for medical image indexing and therefore it has been experimented local Gabor filter-based features extraction on cardiac MRIs. In the future, an extension of that kind of filter to 3D and/or multimodal images would be interesting to benefit from all information available in medical images.

The experiment described in this clinically relevant information can be extracted out of the images without (i) any user supervision (ii) nor fine parameter tuning for a specific purpose. Local features extraction on a per-tissue basis enables the study of clinically relevant parameters such as the myocardium contraction evolution along time. It demonstrates that some semantic interpretation of the image can be accomplished through low-level textural information extraction and classification. Texture filters are therefore interesting for accomplishing general purpose medical image indexing although high level query tools will need to add domain-specific knowledge to perform queries responding to specific clinical requests.

By storing clustering patterns along with the low-level features set in a unified format we facilitate further processing and analysis. To date, most data mining algorithms have concentrated on the extraction of interesting rules directly from low-level data [43]. The approach proposed in this manuscript provides the means for deriving rules from the results of other data mining algorithms that is, mining from rules set. In the current work our initial low-level feature set is further processed and represented via clustering by higher-level patterns which are in a machine processible format. A significant advantage of this approach is that the nature of the rules to be extracted by this process contains different higher order semantics.

Conclusion

Future perspectives of this work include: a) the systematic evaluation of the proposed scheme for the retrieval of various medical images, such as endoscopic [44] and ultrasound images [45] according to their pathology, b) the enhancement of the retrieval performance by using image indexing techniques based on specialized data structures [46]-[47], c) the integration of the proposed scheme with ontology-based information extraction and data mining techniques for the retrieval of medical images using heterogeneous data sources.

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