INFORMATION MINING IN MEDICAL IMAGE DATABASES

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Abstract: The diagnose methods based on medical images are constantly expanding. For easily accessible databases deals with more and more problems, due to the fact that the medical information must be retrieved no matter which technical method was used to acquire the image. The queried information must be also achieved for any imaging orientation, for different body regions, considering the analyzed biological system. In our study we have applied a Content-Based Image Retrieval (CBIR) system, implemented for earth observation images, to archive and to administrate a medical database.

Introduction

The methods that use the medical images for diagnosis are continuously developing. It is therefore necessary to design databases for these images in such a way that the medical information can be retrieved no matter which technical method was used when the image was recorded. The information must be also achieved for any imaging orientation, for different body regions, considering the analyzed biological system [1].

The challenge in medical informatics is to develop tools for analyzing the content of medical images and to represent them in a way that can be efficiently searched and compared by the physicians. There is an increasing trend towards the digitization of medical imagery and the formation of valuable archives. Among the technology to access such data bases is the Picture Archiving and Communication Systems (PACS). It is available within a hospital allowing global access to shared resources [2].

One of the most important components of a PACS is a Content-Based Image Retrieval (CBIR). CBIR system shall be designed so that the information the physicians are looking for is self-contained. In order to support exploratory queries, i.e. information mining considering huge medical image databases, all approaches for CBIR systems compute a certain set of features being stored in the database and linked to the original image. Regarding the integration of CBIR systems into PACS, there is no need to analyze whether these features are global, local, and hierarchical or of other more complex structure. This information is integrated internally by the CBIR system. The CBIR system must have an interactive graphical interface for data entry and a mechanism for relevance feedback and query refinement.

In our study we have applied a CBIR system implemented for earth observation images [3], to archive and to administrate a medical database.

Processing Methods

The diagram in Fig. 1 presents the simplified architecture of a modern image communication system [4].

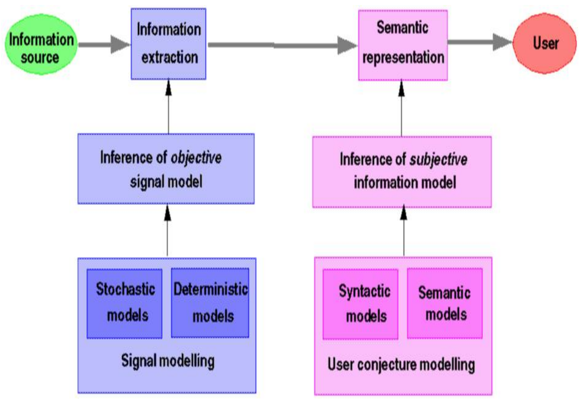

Figure 1: Architecture of an image communication system

The information source is assumed to be a collection of multidimensional signals, e.g. satellite or medical images. The information retrieval process is split up in two steps

- objective information extraction
- semantic representation

The KIM (*Knowledge-driven Information Mining*) system used in this study consists of three main subsystems: *a library of algorithms* that is used to extract the primitive features like spectral signatures, texture parameters, or geometrical attributes, of all images ingested in the system and to represent them in a condensed format; *a machine learning (Bayesian*

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network) algorithm used in conjunction with a graphical interface operated by the user to generate interactively image classifications; *a database management system* which stores and manages an image content information catalogue and records the semantic and knowledge derived by the user when doing classifications or searches in the image repository [5].

KIM integrates new concepts with methods and technologies of Internet communication, data base management systems, stochastic modeling, image understanding, learning paradigms, semantics and knowledge representation, thus enabling queries at an increasing level of abstraction, complexity and answering difficulty (requiring more and more reference to some body of external knowledge), corresponding to the increasing complexity of the related attributes, which can be classified from low to high complexity

- Basic attributes**:** instrument or sensor imaging mode or parameters.
- Primitive features: intensity, texture or shape, i.e. attributes that are both objective, and directly derivable from the images themselves, without the need to refer to any external knowledge base.
- Derived features**:** sometimes known as logical features, these are objects of a given type or specific object. This level involves some degree of logical inference about the identity of the objects and permits searches in user semantic terms (which can be assigned during system training to weighted combinations of primitive features).
- Abstract attributes: involving a significant amount of high-level reasoning about the meaning and purpose of the objects or scenes depicted (e.g. illegal plantations). They are outside the scope of the current research activity.

The concept applied in KIM is aiming at building a system free from application specificity, to allow its open use in almost any scenario, and also to accommodate new scenarios required by the development of new sensor technologies or growing user expertise. These goals are reached by defining a hierarchy of information representation, as presented in the illustration below, permitting the communication between an image archive and the users.

The system is based on human-centered concepts (HCCs), allowing new visual user interfaces. The solution implemented by KIM combines the strong skills in judging and using native intuition of the human operators with the power of the computers to solve complex mathematical problems, being an efficient tool in archiving medical databases. Images contain quantitative, objective information whereas people can understand them only in the form of symbols (ω) and semantics (Λ) in a semiotic context. This models the perception of the observed image, *y*, by an analyst in the context of a given task.

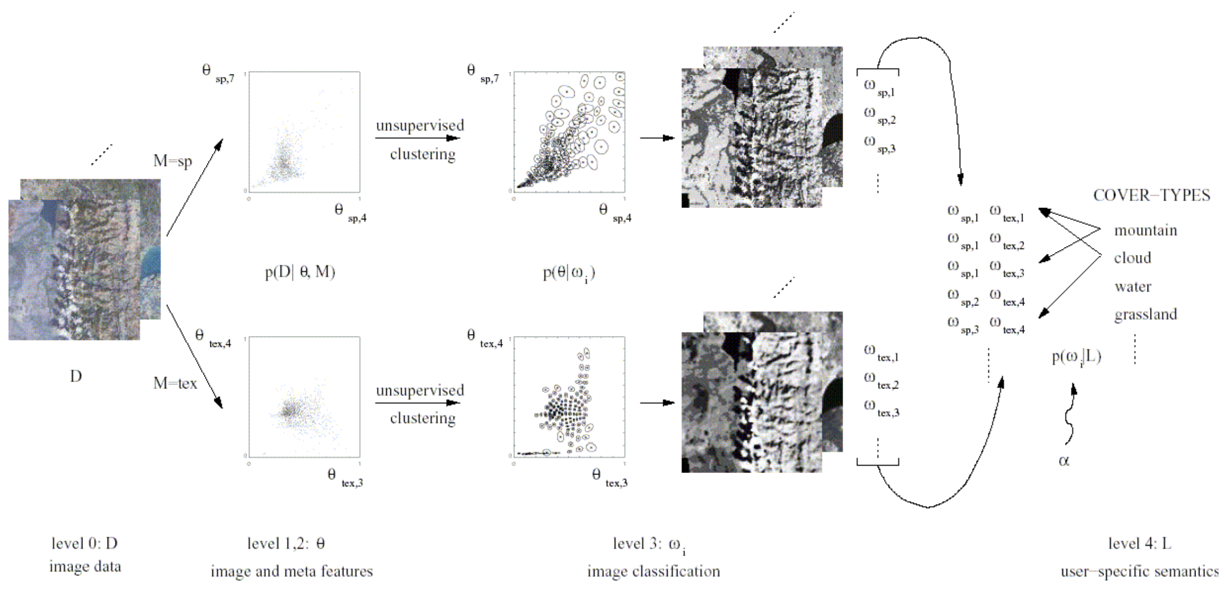

Figure 2: Hierarchical modeling of image contents and user semantics. The image data (level 0) is processed for extracting the primitive features and meta features of the image (levels 1 and 2). Information at level 1 is represented as a parameter vector of a signal model. The specific signal model is the level 2 of information representation. Further, we obtain by unsupervised information clustering a characteristic vocabulary of signal classes (level 3) for each signal model. User specific interests, i.e. cover type labels, are linked to combinations of these vocabularies using simple Bayesian networks. Levels 1 to 3 are obtained in a completely unsupervised and application-free way during data ingestion into the system. Users using a learning paradigm can interactively define the information at level 4. In an additional step of stochastic modeling, we describe the stochastic link between signal classes and user (subjective) labels using a vector of hyper-parameters.

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This modeling results in three processing steps. First, the basic information is extracted, the semantic at this level involving only the selection of the type of the algorithm used to extract the information.

Then the extracted information is gathered to define object components and contextual structures. Supervised learning techniques are used at this level, image labels being settled by the user.

Finally, at the last level of abstraction, where the interpretation is mainly cognitive, the scene is understood as an ensemble of objects in a determined context.

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User specific interests, i.e. image structures and labels, are linked to combinations of these vocabularies using simple Bayesian networks. Levels 1 to 3 are obtained in a completely unsupervised and application-free way during data ingestion into the system. Users using a learning paradigm can interactively define the information at level 4. In an additional step of stochastic modeling, we describe the stochastic link between signal classes and user (subjective) labels using a vector of hyper-parameters.

The first step is the extraction of primitive features and the condensation of the resulting data into primitive feature clusters. The primitive features are carefully selected, since they mainly determine the quality and capabilities of the resulting system. Optical or X Ray images, for example, are handled differently and primitive texture features are extracted at various resolution levels, since different textures can dominate at different scales.

To ensure quasi-completeness of the extracted primitive features the following models are used:

- spectral or polarimetric primitive features to characterise multi-channel sensor data
- multi-resolution to generate a pyramid of different resolutions of each sub-scene such that the various textures and geometric features are identified at the related scale
- texture analysis of optical images by extracting their primitive features using the Gibbs Random Field approach
- coherent image information extraction, providing a de-speckling of images and extracted primitive features using a non-stationary Gauss-Markov Random Field approach
- segmentation by geometry as the homogeneous areas that can be detected in geo-coded images will be assimilated to reference shapes and related to an absolute co-ordinate system

Primitive feature extraction generates a huge amount of data, which cannot be handled in practice and therefore has to be compressed somehow. Each pixel of the image will be located in n-dimensional space in the position determined by the values of the contributing primitive features (their units are non-commensurable, e.g. texture and spectral features). The features will tend to group themselves into specific regions of this space. Through clustering the clouds of image primitive features are replaced by stochastic models of their groups, which can be represented in more compact forms. This is similar to a quantisation process, and determines the accuracy of the mining functions.

In contrast to other pattern recognition methods, the clusters (condensed representations of primitive features) have no direct meaning; they represent characteristics of the image seen as a multi-dimensional signal. The semantics is associated by weighting and grouping the cluster models, similarly to the words of a vocabulary to build the meaning in a sentence. This is a user centered and interactive process, an information-mining function, involving a learning phase.

The system presents sample images in which the user marks areas with positive and negative traits, refining the definition of the derived feature through an iterative process. Once this process/system training has been satisfactorily completed, the definition can be saved and used by other users, who then will have only to request images containing the derived features corresponding to that definition.

A Bayesian network links primitive feature clusters and definitions and these associations can be stored and made available to users for subsequent interactive sessions. The man-machine dialogue is based on visual communication, and visual relevance feedback, and accompanied with powerful information theoretical (mutual information) and statistical measures (MAP values, separability of the posterior models).

With this approach, we are modeling and learning about the user interests and actions, we developed a system that adapts to the particular interests of the users and incorporates contextual information to determine the user's intentions and his/her degree of satisfaction with the results. It should provide a breakthrough by establishing a new pattern for user - system (archive) interaction, and a big leap with respect to the more traditional feature-extraction systems. The aim with KIM is to help users to uncover the most relevant image information content, by providing an eye allowing to delve into multi-sensor and multi-temporal image data archives.

Results

The analysis and interpretation of dermatological structures is a high complexity process, difficult to be automated. There are at least two classes of problems: objective ones, i.e. signal processing and subjective ones, i.e. regarding the interpreter conjecture

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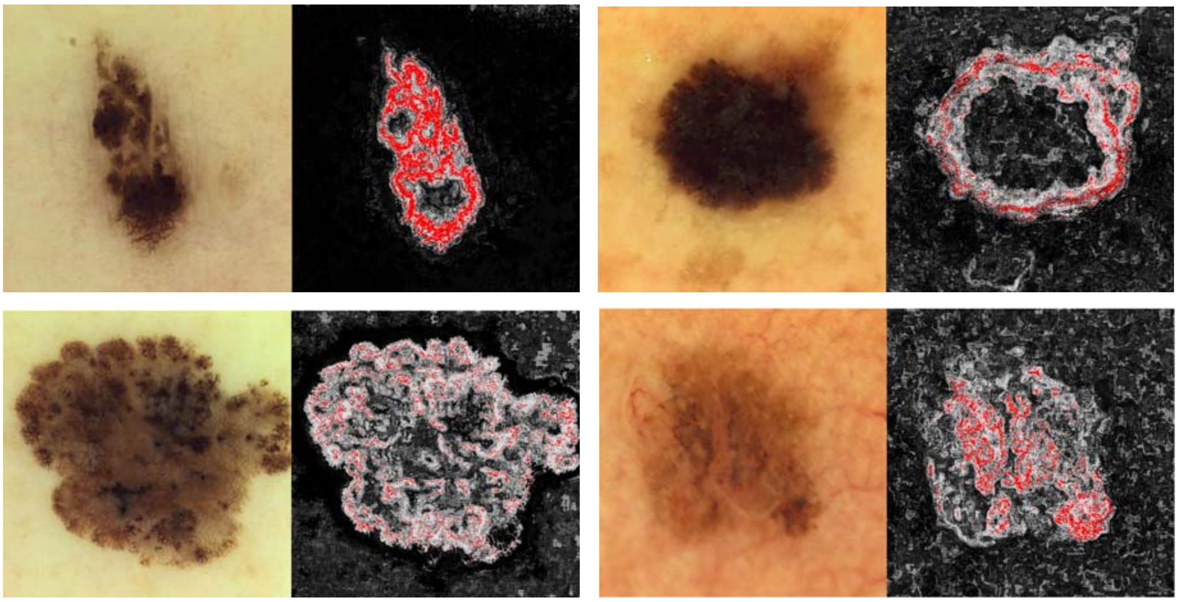

Figure 3: Probabilistic retrieval for the "pigment network" label

Image analysis of skin structures is hindered by many factors

- illumination and pigmentation variability
- large diversity of texture like patterns
- the ambiguities of "texture" parameter matching with the visual recognition of a certain "pattern"

Thus, in the diagnosis the interpreter integrates important domain knowledge, which is difficult to be realized automatically.

A set of images was processed and analyzed using interactive learning and probabilistic search functions. An example is presented in Fig. 2. These preliminary results demonstrate the power of classification using fusion of colour and texture information, and the usefulness of generalization for understanding of the nature of the structures in the image. However, the understanding of observations of unknown structures needs models, experience, and special knowledge.

In the case of medical imaging, it is the radiologist having a special talent for looking at a fragment of information in two dimensions and extrapolating it to three. In his/her mental eye, he/she can create an entity from a single section or slice.

Conclusions

The method used in the study to access a heterogeneous medical database provides accurate access to the medical images of interest.

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