

AUTOMATIC EXTRACTION OF SEMANTIC CONCEPTS IN MEDICAL IMAGES

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ABSTRACT

A novel automatic system for extracting the semantic descriptions of medical image content and concept in text form is presented. We first extract and analyze image features and the features are mapped to semantic descriptions by fuzzy functions. Based on these semantic descriptions, our system facilitates knowledge base construction using a machine learning scheme. The result will be useful for other researchers in medical image retrieval area, who can take advantage of both text-based queries and image queries.

1. INTRODUCTION

Medical information systems with advanced browsing capabilities play an increasingly important role in medical training, research, and diagnostics. Many medical Picture Archiving and Communication Systems (PACS), for example, contain several terabytes of on-line medical image data [1]. However, the utilization of such data for research and education is limited by the lack of intelligent, effective retrieval capabilities.

There is no doubt that robust content-based retrieval will prove valuable to the medical imaging field, but one must first provide appropriate descriptions of image content and corresponding measures of similarity, such that medical images can be compared based on their features and their meanings.

This paper presents a prototype of semantic concept extraction from medical images. The emphasis of this paper is to map between image features and image concepts. We limit the scope of our work initially to projection chest radiographs.

2. SEMANTIC CONCEPT OF MEDICAL IMAGE

To describe the semantic concept of image more precisely, let us define f as mappings from images to image features, s as mappings from image features to image semantic features (attributes) and q as mappings from image semantic features to image classes.

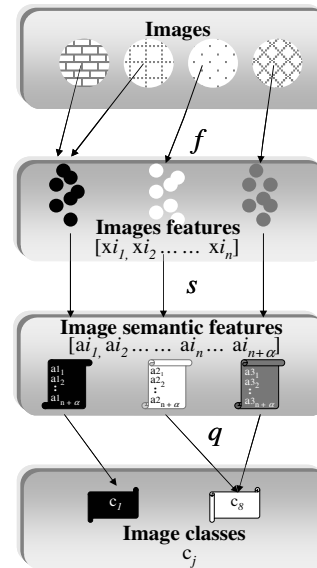


Figure 1. Mapping diagram from images to image classes

Liu *et al.* [2] proposed the concept of a semantically well-defined image set:

1. There is a finite number of possible distinct image classes (no arbitrariness) defined in the set.
2. Any pair of image classes is mutually exclusive (no ambiguity).
3. Each image corresponds to one class and one class only.

As Figure 1. shows, after we extract image features (x_1, x_2, \dots, x_n) from images, features are mapped to a certain symbolic descriptions $(a_1, a_2, \dots, a_n, \dots, a_{n+\alpha})$. In this step, we suppose there is a semantically well-defined feature set. However the most important characteristic of a medical image retrieval system, unlike a general image retrieval system, is the meaning of the image. Therefore, based on these semantic features we infer the meaning of the features to suggest the possible diseases (c_i) of the input radiograph. In this step, there is no semantically well-defined image set since a finite number of classes can not be defined and the images with different features can be classified to the same class. Therefore we define the semantic concept \mathcal{K} of medical image (I_i) as

$$\kappa(I_i) = I_i \cup s(f(I_i)) \cup q(s(f(I_i)))$$

I_i is an input image, $s(f(I_i))$ results in the image semantic descriptions $[ai_1, ai_2 \dots ai_n \dots ai_{n+\alpha}]$ in text form when n lung abnormalities are automatically extracted by image processing tools and α features are manually extracted by interacting with radiologists through a Graphical User Interface. $q(s(f(I_i)))$ results in the class c_j of I_i in text form includes the possible diseases. Therefore, our final result $\kappa(I_i)$ includes an image, semantic descriptions of image and possible diseases. The image can be retrieved by queries such as ‘retrieve lung X-ray images with big hilar region and grape-like pattern’ or ‘retrieve lung X-ray images containing thoraxpneumonia’.

3. SYSTEM ARCHITECTURE

3.1. Overview

Our system consists of three levels, which are low-, intermediate- and high-level processing (see Figure 2). Low-level processing includes a number of image analysis algorithms such as lung segmentation, texture analysis, ribs and clavicle detection and hilar region detection. Intermediate-level processing symbolizes and describes the image features obtained from low-level processing for recognition and interpretation of image features. High-level processing has a stronger resemblance to what is generally meant by the term ‘incremental knowledge’.

3.2. The main modules

3.2.1. Image processing

Most of the image features are automatically extracted by image processing tools in our system but some of them is very hard to extract, for example, ‘lung texture behind heart, but these features are also required to suggest the possible disease. Therefore, to reduce the risk caused by low-level processing, our system allows interaction with radiologists to manually extract the features through a user interface (processing3 in Figure 2).

Image processing produces image features in the form of numeric data (ie., 3cm: height of left hilum above the right) which should be converted to text data (ie., high: height of left hilum above the right) and processing1 in Figure 2 shows the case, and text data (ie., Grape-like: lung texture) which is not needed to go though the symbolic processing (see processing2 in Figure 2). There are four modules: lung segmentation [4,5], texture analysis [6,7,8], rib detection [9], and hilar detection [10], The details of the algorithms can be found in our previous papers [4,5,6,7,8,9,10].

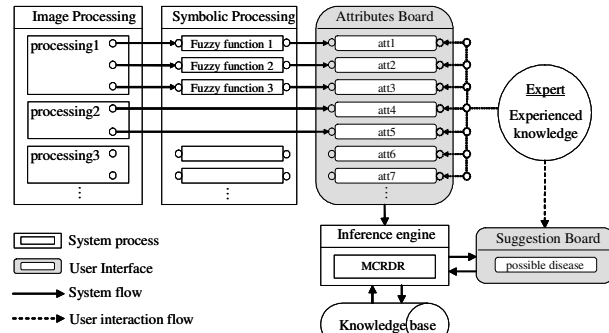


Figure 2. System overview

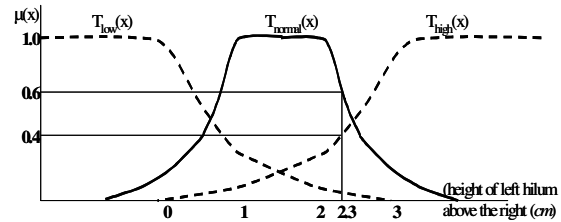


Figure 3. Fuzzy sets for the height of the left hilum above the right

3.2.2. Symbolic processing

In order to allow high-level symbolic processing, the descriptions of features are defined so that some of them, such as ratio, presence, position, width, size, angle, and density can be represented in linguistic terms. Fuzzy logic is fundamental if one wishes to model terms involving vagueness or imprecision such as ‘abnormal’ or ‘high’. In this paper, we adopt the fuzzy expert system (FES) concept introduced by Buckley [14]. A number of FESs have successfully been implemented to-date and we use the triple formed by the Z-function, the Π -function and the S-function for defining fuzzy membership functions.

For example, in Figure 3, a height of 2cm would be described as normal ($\mu(x), 1.0$), and a height of 2.3cm has $\mu(x)$ of 0.6 in the normal set and it has $\mu(x)$ of 0.4 in abnormally high, so the system might return a ‘slightly high’ as the linguistic value, when $\mu(x)$ is the membership function. In this way, the radiologists, who provide the chest radiograph information need for both delineation and recognition of image features, can work with statements with which they are familiar with, based on nonnumeric descriptions (i.e., linguistic terms) of object features.

3.2.3. Inference

Our system employs Multiple Classification Ripple Down Rules (MCRDR) to facilitate knowledge base construction to diagnose the possible diseases based on the symbolic descriptions which describe the radiologic finding from the chest radiographs [3].

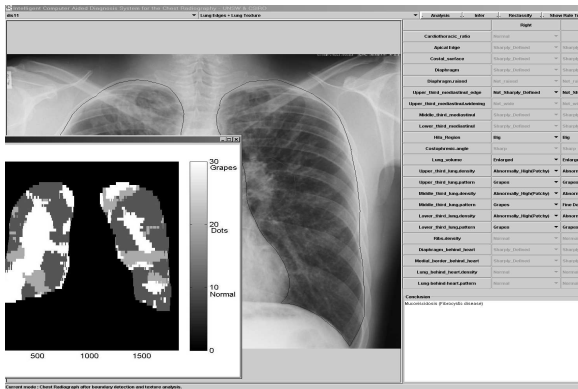


Figure 4. ICAD application for chest radiograph

Observation of experts during maintenance suggests that experts never provide information on how they reach a specific judgment. Rather the expert provides a justification that their judgment is correct. The justification they provide varies with the context in which they are asked to provide it [11]. MCRDR is an incremental knowledge acquisition technique whose aim is to only use the knowledge in the context provided by the expert; this context being the sequence of rules evaluated to give a certain conclusion [3]. Therefore, all rules in our system using MCRDR have been added by radiologists without any knowledge engineering or programming assistance or skill. In other word, the radiologists construct, maintain and increase the knowledge base by themselves without engineers' supports.

A MCRDR knowledge base (KB) can be described in terms of courteous logic [15]. A courteous logic program contains two parts, namely, labeled clauses and Overrides statements, which permit the establishment of a priority-based policy amongst the rules in a KB. A statement *Overrides(P,Q)* means that the conclusion of the rule *P* will take over the conclusion of the rule *Q* in an inference process. Then a multiple conclusion (mc)-rule is characterized by the following two courteous rules:

$$\langle R \rangle \text{ Conclusion} \leftarrow L_1 \wedge L_2 \wedge L_3 \dots \wedge L_n$$

$$\langle C \rangle R \leftarrow C_1 \wedge C_2 \wedge C_3 \dots \wedge C_m$$

where L_1, \dots, L_n are Boolean conditions derived from the input case; C_1, \dots, C_m are the cornerstone cases associated with the rule *R*. The cornerstone cases of *R* are recorded during the addition of new rules. When a new rule *R'* is added to the system, the rule *R'* should contain the differences among the cornerstone cases that satisfy the rule and the input cases. In order to exclude a further case when other stored cornerstone case satisfy the rule, additional conditions must be added. The process is repeated until there is no stored cornerstone case satisfying the rule. In case that a conclusion of the new rule *R'* replaces the conclusion of *R*, we have to add an

ID [dis06]
Right Apical Edge [Sharply Defined]
Right Diaphragm [Not Sharply Defined]
Left Diaphragm [Not Sharply Defined]
Right Upper third mediastinal edge [Not Sharply Defined]
 :
 :
Left Lower third lung density [Abnormally High(Patchy)]
Right Ribs density [Abnormally High]
Left Ribs density [Abnormally High]
Class [Left Ventricle failure Influencing dense ribs Old inflammatory change at the right apex, bullous change at the left apex Ischemic heart disease and CAL]

Figure 5. Image description in text form

Overrides(R', R) statement to the KB. If the conclusion of *R'* is new, then no Override statement is added.

3.2.4. Attribute board: user interface

Radiologists use expert knowledge in performing diagnosis. It is a large and difficult task to summarize that knowledge and represent it properly in a computer user interface. The main difficulty is that the process involves perception and cognition knowledge, which is difficult to quantify and measure as physical features. We have made some efforts in this respect and have built an application called intelligent computer aided diagnosis (ICAD) system for communication with radiologists to form and to computerize their knowledge [12]. Therefore, the interface is designed to allow radiologists to interact directly with the system (see Figure 4). The user interface consists of four boards: image board, control board, attribute board and conclusion board. Image board displays the input chest radiograph, the boundary of the lung field, the hilar region, and the texture of the lung field. The control board includes all menus that can be selected by radiologists to control all the other boards. Attribute board shows all attributes with a selection list. The attributes are automatically enabled by image processing if there are any abnormalities and they also can be enabled by the radiologists and the abnormalities listed in Figure 5.

4. RESULTS AND DISCUSSION

Our results were verified by an experienced radiologist. The results from image processing are not detailed here and can be found [4,5,6,7,8,9,10].

system: We tested 33 chest radiographs including 5 normal cases and 28 abnormal cases. ICAD detected all 5 normal cases, so our system had 100% success rate for detection of normal chest radiographs. ICAD detected 260 abnormalities while the radiologist detected 326 abnormalities in abnormal cases. The result included 213 true positives, 47 false positives and 113 false negatives. Therefore, the sensitivity of the automatic radiologic

finding is 65%. This relatively low sensitivity is biased by poor performance for some abnormalities (e.g., dots texture detection, hilar detection, etc.) while the sensitivity for 'high rib density' was 100% and for grapes texture was 95%. To increase the system sensitivity, more sophisticated image feature extraction methods are required.

symbolic description: Since we are approximating an expert level of belief we have generated the fuzzy compatibility functions manually with guidance from a radiologist. The range from low limits and high limits of function are a long way apart since the image features are flexible, i.e. highly deformable. Thus, the model indicates that under normal conditions the relative image features are quite well-defined, but a wide range of abnormal variation is possible.

inference: MCRDR is a commercial product developed by Pacific Knowledge Systems and the first product LabWizard was released in 1998 [13]. The performance reports for the Lipid knowledge base created and maintained by one of their customers shows that the pathologists created a 7,000 rule knowledge base over the course of 30 months and total time to add rules was 100 hours 8 minutes. Instead of the industry average of 2-5 rules per day, LabWizard users can add 1 rule per minute. We tested our system with 31 PA radiographs and 28 rules. The radiologist built the knowledge base for our system to add a new rule or to modify a current rule only requires a minute time for typing a new conclusion and it was simply done by 'reclassify' key through ICAD interface. Therefore, we found the rules are easily constructed, modified and improved by the radiologist.

semantic description of image contents and concept: After the image analysis and classification by system, the final result, which is what is most useful for querying, is stored in text form as in Figure 5. The format of this file is simple: *ID* represents the image identification, followed by *Attribute [Attribute value]* and the attributes representing the abnormalities of the image, and finally *Class* which represents the possible disease. This document can be easily reformatted by the engineer for application access within a different 'information retrieval system'.

5. CONCLUSION

We have proposed a method for automatic extraction of semantic concept from medical images. So far, the utilisation of online medical data is limited by the lack of effective indexing and categorization methods. Therefore, we provide the system that can automatically produce the semantic descriptions of image contents and the concepts of images. In particular, the image query is possible since our system extracts the semantic concepts including image

features and possible diseases from the query image. Thus the text descriptions of the query image can both be used as data or can be used as a query to find similar images. Therefore, these results will be useful for other researchers in medical image retrieval area, who want take advantage of both text-based queries and image queries. Existing databases and multimedia information retrieval systems can also be easily approached or expanded to medical image retrieval issues by our proposed method.

6. REFERENCES

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