A New Knowledge-based Lung Nodule Detection System

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ABSTRACT

In this paper, we describe a knowledge-based system for segmenting and labeling lung nodule on CT images. The system was developed in a blackboard environment that incorporates lung knowledge model, image processing model and inference engine. Lung model, which contains anatomical knowledge about lung in the form of semantic networks, is used to guide the interpretation process. The system works in a hierarchical structure, from large structures to the final nodule candidates, by focusing on the interested region step by step. The symbolic variables introduced to accomplish high-level inference, are defined by fuzzy confidence functions in lung model. Composite fuzzy functions are used to map between image and lung model objects. Anatomical lung segments knowledge is embedded in the system to direct 3-D validation of suspicious objects. Structures are identified and abnormal objects are reported. Preliminary experiment results are included.

1. INTRODUCTION

Lung Cancer is currently the leading cause of cancer deaths in the United States, with only 13% 5-year survival rate [1]. Helical CT system is capable of performing the scan and image reconstruction simultaneously and also high-resolution CT has been proved to be effective in characterizing edges of pulmonary nodules [2]. So, our research objective is to develop an analysis module for early lung nodule detection by using helical CT image.

But detecting nodules is a complicated task because of the various shapes of nodules on the CT images. Experience has shown that many real world problems are not amenable to simple universally applicable methods unless additional knowledge is included. Numerous systems have been reported that use anatomical knowledge, in the form of constraints on features such as expected size, shape, texture, to perform image interpretation. Typically segmentation is based around threshold, edge detection and feature-based pixel classification. These systems are effective and useful but do not provide a high-level representation of the image content. Also, anatomical knowledge is embedded within the segmentation algorithms, making it difficult to extend to other problems. In our system, the anatomical knowledge is stated explicitly in a lung anatomical model that is independent of the image processing routines. The anatomical knowledge and image processing routines are combined in a blackboard system.

The organization of this paper is as following: Section 2 briefly introduces the semantic network, which acts as knowledge base in the nodule detection system. Sections 3 and 4 mainly illustrate the nodule detection system that is embedded in the blackboard architecture. Section 5 presents preliminary results and analysis, followed by conclusion.

2. LUNG MODEL IN SEMANTIC NETWORK

In our research, the structure of the lung model is built as a set of contiguous 2-D images of parallel CT slices through the thorax representing the 3-D anatomy. We used a semantic network to incorporate the anatomical knowledge into an automatic nodule detection system.

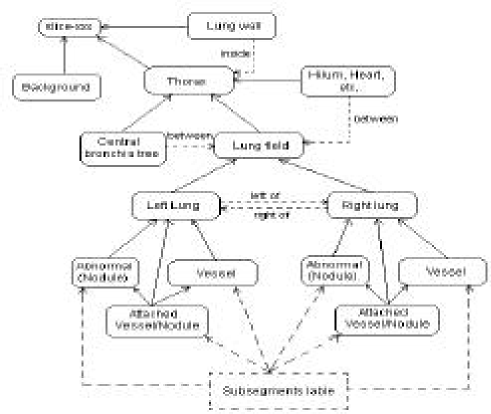

Fig. 1 Semantic network

The 2-D model describing the structure and features in each slice is organized into a hierarchical semantic network structure where each node represents a lung object and the descendant nodes are subparts of the object. Fig.1 is a simplified description of a 2-D lung module for one slice. Features representing lung structures describe terminal and intermediate nodes. The nodes are used later during the interpretation process to match lung and image objects. The spatial relationship constraints are defined only among the nodes stemming from the same parent in the hierarchy (see dashed lines in Fig.1).

At each level of the hierarchy, a 2-D object instantiation is described using several features. Generally, at higher level, which mostly includes large areas such as background, lung wall and thorax, fewer features are used because these structures are relatively easy to be segmented. As the level moves down, the objects are confined in a much smaller area with more likely having similar image property and so more features are needed to deal with the similarity. For a high-level image analysis, a high-level representation must be derived. In our approach, the interpretation involves transforming low-level representation of features described by numerical parameters to high-level representation using fuzzy sets. By setting confidence functions, fuzzy sets provide an intuitive means of modeling anatomical variability and allow the model to impose soft constraints on the segmentation and matching.

According to the bronchial anatomy, the lung lobes can be sub-segmented to several parts as shown in Fig. 2 [3]. The smallest functional unit of the lungs is the bronchopulmonary segment [4].

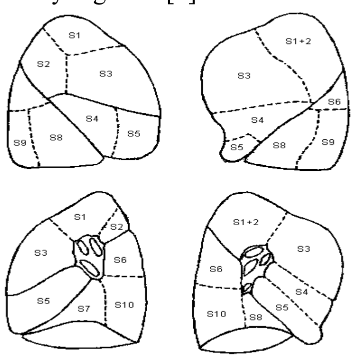

Fig. 2 Bronchopulmonary segments

The bronchi and blood vessel in each segment are relatively independent to those in adjacent segments. The sub-segments knowledge was used for 3-D localization of lung nodule candidates in the system. The dashed line and "sub-segments label" module are used for 3-D object interpretation. The links to the 2-D instantiations by the "sub-segments label" indicate in which slices 2-D cuts of a particular 3-D structure are typically perceived. They also indicate which context information can be shared among different slices.

The sub-segments labeling only applies to the terminal level of the model, in this level, all the candidates are in lung field, they are nodule or blood vessel, each candidate will be associated with a specific sub-segment. In our automatic detection system, if a candidate can't be classified by its 2-D features, a further 3D validation will be applied.

3. SYSTEM ARCHITECTURE

The system architecture which includes several modules is shown in Fig. 3.

-- The blackboard (BB): the central workspace, a temporary database that is continually constructed and updated along the inference process. The dashed line represents the abstraction hierarchy of inference process, with the original image input at the lowest lever and a mapping report at the highest.

-- Lung model knowledge base: it stores the semantic networks described in Section 2, which contains the descriptions of lung objects, such as their image characters and relationships.

-- Operator scheduler (OS), which contains lists of different sequence of image processing routines for each specific problem. It invokes different image processing routines from image processing library.

-- Information extractor (IE), which acts on BB for feature extraction and feature conversion. It extracts information from image board and sends it to feature board for further processing.

-- Image processing library, which contains different image processing routines that can be invoked by OS and IE.

-- Inference engine, which collects information from feature board and lung knowledge source, matches the candidates to best fitted model, that is, matching image objects to lung structures stored in lung knowledge source.

-- Temporary storage, it stores description for each nodule candidate, which can be used for 3D validation for more accurate classification.

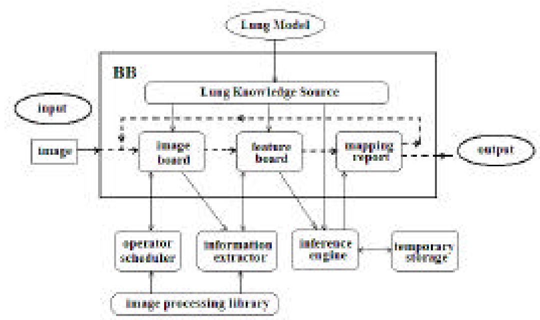

Fig.3. System architecture

The blackboard workspace is arranged in a three-level hierarchy in order of increasing abstraction.

-- Image board: all images that include original image, processed image, temporary image, etc., are stored in the image board. Lung knowledge source and OS work together on the image board, from original input image, they produce necessary subsequence images for further process.

-- Feature board: It is the place where feature description of each image region or candidate is stored. The description which are derived from the image board by IE are embedded in a frame based structure. Lung KS provides information about what kind of features should be extracted for a specific case in each step.

-- Mapping report: This module is a report space that contains partial and final mapping result for each candidate.

-- Lung knowledge source (KS): the lung description information that is input from lung model is stored in this module, which is involved with every step of the inference.

4. IMPLEMENTATION

The system operates in "step" and on each step, the lung model and image process modules exchange necessary information through the blackboard. Lung model provides information about the kind of image candidates to be segmented and the kind of features to be extracted. According to the information that is posted on blackboard, image process modules operate on images. According to the extracted features, each image candidate is matched to a specific lung anatomical structure that is modeled in lung KS by inference engine. The nodule candidates are stored in a temporary storage. If a nodule candidate can't be classified by 2-D features on single slice, then the inference engine accesses its corresponding candidates on adjacent slices to make a 3-D validation.

A. Work on image board

According to the slice number, blackboard accesses lung model and save the corresponding lung semantic network in lung knowledge source. By collecting information from semantic networks, the operator scheduler chooses different algorithms and parameters. For each level in the semantic networks, we set a sequence of image processing according to our stand-alone trial and error experiments. The algorithm lists are stored in operator scheduler, when a certain level is scheduled for segmentation, image board invoke the sequence of algorithm from the list.

The current system starts with a simple global gray value thresholding to separate the background and lung field. At the second level image processing, the system will focus on a finer subdivision of the lung. A k-means clustering technique [5] was then used to automatically segment a CT slice into lung field and regions containing the lung wall and mediastinum. Some of the nodules adjacent to lung wall may be excluded from the extracted lung field. To alleviate these impairments, we used the method described in [6]. At the final level, nodule candidate segmentation in the lung field, a fuzzy C-means algorithm [7] was applied. One problem after the lung nodule candidate segmentation is that different structures within lung can merge into a single connected region. The result is multiple objects merged into a single larger object. In order to reduce the distortion due to merging, a binary splitting [8] is performed on the detected objects.

B. Feature extraction

The second level on the blackboard is feature extraction. Lung KS posts what kind of features should be extracted, IE access the feature board and extract different features from image board for each candidate and post these features back to feature board for further inference. In the current system, candidate's features are stored on feature board in a frame-like manner, one frame for one candidate. The frame encapsulates all the information related to a candidate into one package, significantly simplifies the data flow and control on blackboard. The features include: 1) shape and size features, such as area, perimeter, width, height, roundness, smoothness of margin, orientation. 2) statistic features, such as mean gray value, standard deviation of gray value, minimum and maximum gray value. 3) location features: distance from boarder/structures, centroid, locations in sub-segments, spatial relationship with other regions, etc.

C. Inference engine

The main function of the inference engine is to classify image candidates to lung structure. In order to allow high-level interpretation process, some features in lung model, such as size, position, roundness, are defined by fuzzy set. IE converts some features to symbolic term according to the fuzzy set stored in lung KS. The interpretation of lung CT implies finding an acceptable mapping between image and objects in each level. The elegance of fuzzy set is that they can be combined to produce a composite constraint function, defined as a normalized weighted average of different simple confidence functions associated to its feature.

In this preliminary research, the fuzzy confidence functions and composite constrain functions were determined empirically with guidance from trial and error experiment.

D. 3-D validation

In the analysis of 3-D objects, it is desirable to detect the relative position of interested anatomical structures on different slices. One way to achieve this is to register the image to a model of the depicted structure. In this system, each nodule candidate was registered in specific bronchopulmonary sub-segment. These segments can be matched on 2-D slices by prior knowledge. Fig.4 shows different segments on different slice.

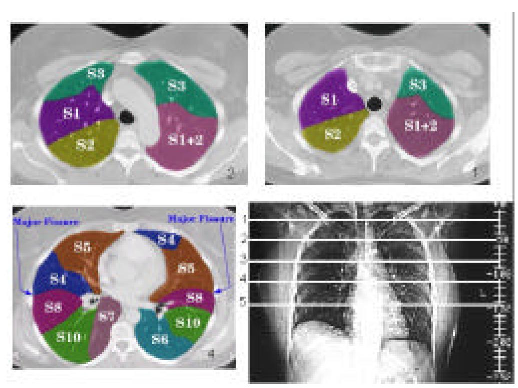

Fig.4. Segments on different slice

With these knowledge, we associated the nodule candidates to specific sub-segments on each slice and assigned an elastic coordinates to each candidate within the sub-segments. The sub-segment labels and coordinates act as index for searching candidates in 3-D manner. The sub-segment label and coordinates of each nodule candidate are stored in the candidate's frame, and all the frames are stored in temporary storage. The system accesses the 3-D related candidates for a specific candidate according to the labels and coordinates. The advantage of the deformable template is that it significantly increases the speed of the 3-D searching processing. In the current application, the segmentation was carried out in 2-D while 3D information was included after the segmentation. In this system, the 2-D vessel reduction in the first inference step partially solved this problem by first eliminating a large number of vessel structures during the 2-D analysis before forming 3-D object. Once 3-D objects were formed, the following features were extracted for each 3-D object: volume, surface area, average gray value, standard deviation, and sphericity.

5. PRELIMINARY RESULTS AND ANALYSIS

Anatomical structures were segmented and nodule candidates were classified from CT images by the proposed system automatically. The CT images were acquired using LightSpeed scanners with slice thickness of 8 mm. Each image is 512x512 pixels and the gray level depth is 16 bits. To evaluate the performance of the automatic lung nodule detection system, the system was applied to 28 helical CT images of 5 patients, but the test images were not chosen randomly, they were selected with the aim that most of the detectable abnormalities were covered.

In Fig.5, A is original CT image, after a thresholding, the image was segmented to background and thorax in B. C is the right lung nodule candidates. For each candidate, inference engine found the best match according to its composite confidence function. D and E are different result by selecting different weights in composite confidence function, the eliminated candidates were classified as blood vessel and remained candidates were classified as lung nodule candidates. By changing the weights and features combined in composite confidence function, this system imposes soft constraints on nodule detection.

For 3D validation of the nodule candidates, the system accesses relevant candidates on adjacent slices and make a more accurate classification. Anatomical structures were segmented automatically from CT image using the system described. These computer-marked abnormalities were compared against the truth files in which the nodules were identified by a radiologist. The system performance was summarized in Table.1, where a nodule is considered as a positive result. In 2D domain classification, a relatively lax criteria were used to classify the nodule candidates so that the 3D method were emphasized, the false positive (FP) is high in 2D domain, it improved significantly in the 2D+3D domain.

Features based on these 2D structures may not represent the general characteristics of a nodule. In the current system, the candidates classified by 2D features would not be considered after the classification, that is why the false negative in 2D+3D domain is higher than that in 2D domain in Table 1. A better strategy maybe applied, that is, after forming a 3D object, the system can change the classification previously decided by 2D features according to the 3D object.

The results illustrate the potential of the system and knowledge-based methodology. Given the simplicity of the current model, the number of abnormalities that could be identified was encouraging. The design of the system was motivated by a desire to develop a general-purpose framework for knowledge-based medical image interpretation. By adapting to different knowledge source, the system is potentially useful in other applications. However, to be clinically useful the system would need to be expanded to include more subtle structures.

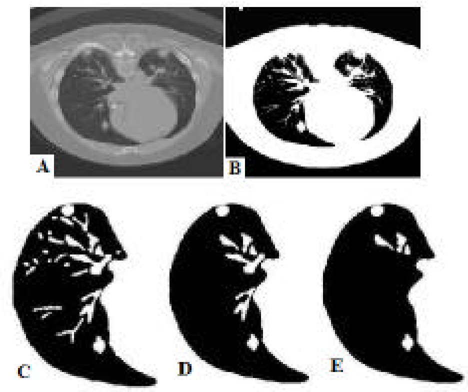

Fig 5. Experiment results of right lung

	2D domain classification		2D+3D domain classification	
	True	False	True	False
Negative	924	3	998	6
Positive	46	96	43	22
Total	970	99	1041	28

Table. 1 Classification results of nodule candidates

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