Multicriterion Homogeneity Metric for Nodule Segmentation and Detection in Computed Tomography

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Abstract — This work proposes a novel segmentation algorithm for lung nodules detection in thoracic computed tomography (CT) which uses more than one criterion in order to decide at each iteration whether two adjacent objects should be merged or not in a region growing procedure. In experiments conducted upon 33 thoracic CTs, support vector machine was used to discriminate nodules and non-nodules. The method achieved 80.9% sensitivity with 0.23 false positives per slice.

Keywords - Computer-aided detection; pulmonary nodule; multicriterion segmentation; computed tomography.

I. INTRODUCTION

The diagnosis of lung cancer depends hardly on successful detection of lung nodules. Computed tomography (CT) of thorax is widely used to diagnostic lung cancer disease because it is a non-invasive method.

Studies have pointed out that radiologists often fail to notice nodules while interpreting chest CT scans [5][10]. This may be due to the large number of slices to be analyzed in a typical CT exam (about 300 slices). In addition, the performance of the radiologist may be influenced by personal problems, fatigue and experience. In this context, computer-aided detection (CAD) has been proposed to facilitate accurate and efficient lung nodules detection [1].

Many segmentation approaches assume object homogeneity. In a sense, segmentation can be viewed as analogous to classification, since the decisions made during both procedures are guided by some known or expected properties of the objects we are looking for. This consideration suggests that some properties relevant for distinguishing objects should guide both segmentation and classification in object detection applications.

This work pursues this conception and proposes a novel segmentation strategy for lung nodules detection in CT scans, where the homogeneity criterion underlying segmentation is expressed in terms of features that well discriminate the object being detected from other object classes present in the image. In our approach, homogeneity is given by a function of highly discriminant features, whose parameters are estimated by a stochastic optimization technique based on reference samples. It is expected in this way that the segmentation does a kind of pre detection that will later improve the final classification step.

II. METHODOLOGY

The proposed lung nodule detection method involves three basic procedures: segmentation, objects description and objects classification (see Fig. 1).

The segmentation is carried out in two steps. First, a pre-segmentation locates the lung region and splits it up into low and high densities. Then a multicriterion segmentation procedure groups homogeneous neighboring voxels into objects, according to some heterogeneity criterion.

The second procedure, called object description, computes the object features. Finally objects are classified as nodule or non-nodule based on their features. Each procedure is described in details in the following subsections.

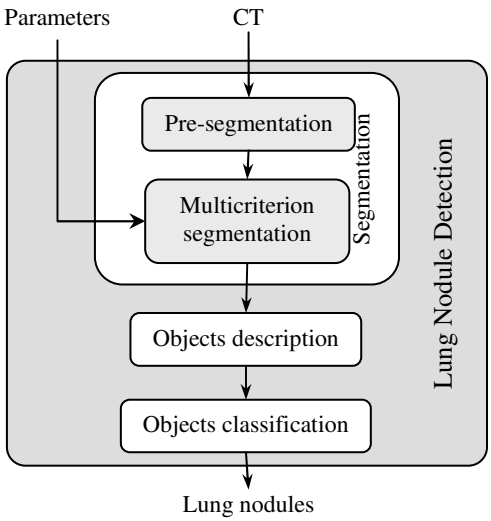

Figure 1. Methodology of lung nodule detection.

A. The segmentation approach

Our segmentation approach involves two phases, called pre-segmentation and multicriterion segmentation, as follows.

1) Pre-segmentation

The main task of pre-segmentation consists of finding the lungs in all CT slices. It reduces the search space for subsequent steps making them faster and more efficient.

The pre-segmentation starts by removing the area surrounding the body through Otsu's thresholding method [7]. Again Otsu's method is applied to remove dense tissues involving the lung, mainly composed by muscles and bones. Then, by using the morphology technique known as *rolling ball* [8], the lung walls are restored so as not to neglect peripheral nodules. The next step consists of masking out the soft tissues, principal constitutive of the parenchyma, preserving only the structures contained in it, what is also performed using Otsu's method.

2) Multicriterion segmentation

The multicriterion segmentation is the key phase in the whole procedure. The algorithm is a stepwise local optimization procedure that minimizes the average heterogeneity of image objects. Objects grow from single voxels or from small segments produced in the pre-segmentation phase, merging them to neighbouring objects. In each processing step, an object can be merged to its neighbour that provides the smallest growth of global heterogeneity. The merging decision is based on minimizing the resulting object's *weighted heterogeneity*, an arbitrary measure of heterogeneity weighted by segment volume.

In other words, a pair of objects is merged forming a new single object if the heterogeneity increase brought by this fusion is lower than a given scale parameter (threshold) (*s*), which influences the size of the objects.

The heterogeneity growth h_k related to feature k (k = 1,2,…,n) resulting from merging a pair of adjacent objects, is given by

$$h_k = v_M \cdot f_{k,M} - \left(v_{Obj1} \cdot f_{k,Obj1} + v_{Obj2} \cdot f_{k,Obj2}\right) \quad (1)$$

where $f_{k,O}$ is the value of the *k-th* feature of object O, v_O is the object volume, the subscripts *Obj*1 and *Obj*2 refer to the adjacent objects being considered for merging, and M refers to the object that would result from merging.

The global heterogeneity H is a function of the form

$$H = F\left(h_1, h_2, \ldots, h_n\right) \quad (2)$$

where n is the number of features to be considered. The definition of the function F is an important issue in the proposed segmentation method.

The present study investigates the potential of the method by choosing a simple implementation of F that is a linear combination of the growth of heterogeneity associated to each feature, i.e.

$$H = \sum_{k=1}^{n} w_k h_k \quad (3)$$

where w_k are weights associated to the *k-th* feature, whereby $\sum_{k=1}^{n} w_k = 1$.

The segmentation procedure merges two adjacent objects provided that the global heterogeneity H does not exceed the scale parameter. The process stops when there are no more objects to be merged.

We believe that this novel segmentation approach can be applied to a number of classification problems as long as appropriate features are chosen. The use of this method for nodule detection is explained in further details hereafter.

a) Selected features for segmentation

The *forward feature selection* method [3] indicated a group of three features for classification, which are used here in the multicriterion segmentation. The features are the variance of voxels density, the spherical disproportion and the elongation.

The spherical disproportion measures surface regularity of objects. The spherical disproportion is small for nearly spherical objects with regular surface and large for irregular or elongated objects. It is given by

$$D = a / \left(4 \cdot \pi \cdot R^2\right) \quad (4)$$

where a is the object surface area and R is the radius of a sphere with the same volume as the object, which is obtained by (5),

$$R = \sqrt[3]{3 \cdot v / 4.\pi} \quad (5)$$

being v the object volume.

The second shape feature is the elongation, defined in (6). The elongation E determines stretching or asymmetry degree of objects.

$$E = Ar_{\min} / Ar_{\max} \ . \quad (6)$$

where $Ar_{\min}$ and $Ar_{\max}$ are, respectively, the smallest and largest edge sizes of bounding box.

Applying (1) to these features yields:

$$h_1 = n_M \cdot \sigma_M^2 - \left(n_{Obj1} \cdot \sigma_{Obj1}^2 + n_{Obj2} \cdot \sigma_{Obj2}^2\right) \quad (7)$$

$$h_2 = v_M \cdot D_M - \left(v_{Obj1} \cdot D_{Obj1} + v_{Obj2} \cdot D_{Obj2}\right) \quad (8)$$

$$h_3 = n_M \cdot E_M - \left(n_{Obj1} \cdot E_{Obj1} + n_{Obj2} \cdot E_{Obj2}\right) \quad (9)$$

where σ^2 is the variance of voxel values and h_1, h_2 and h_3 are heterogeneities for variance, spherical disproportion and elongation, respectively.

Therefore, the multicriterion segmentation algorithm

is fully defined in this case by three parameters: two weights (w_1 and w_2, recall that $w_3 = 1 - w_1 - w_2$) and scale (s). It is worth noticing that the larger the scale the lager tends to be the objects in the segmentation outcome.

b) Genetic adaptation of segmentation parameters

The selection of proper parameter values is crucial for a good segmentation result. This is not a simple issue since generally the relation between parameter values and segmentation outcome is far from being obvious. This is particularly true in our approach where features of completely distinct nature are combined into a single heterogeneity score. This paper uses a method for the automatic adaptation of segmentation parameters based on genetic algorithms (GA) [4] which was proposed previously by Costa et al. in [2].

There are two main advantages of GA in relation to conventional search methods: it is a parallel search and the only requirement is the evaluation function which is described hereafter.

c) Evaluation function

For this application, the evaluation of an individual (set of parameter values) should indicate the similarity level between a segmentation result and the reference segmentation. Once the evaluation function is chosen, the task of the GA consists of searching for a set of parameter values, for which the evaluation value is minimum.

It is known that a same object can be delimited distinctly by different specialists due to the subjectivity and the experience of each one. Therefore, a weight is associated to each voxel of the objects to be used during the parameters adaptation. The weight of a voxel is determined by the ratio of specialists that incorporated it in the object to the total number of specialists. Consequently, the weights range from 0 to 1, being 0 for voxels that were not included by any specialist and 1 for voxels included by all specialists. This work proposes a evaluation function $F(X,P)$ bases on the sum of the weights associated to the voxels as follows:

$$F(X,P) = m^{-1}\sum_{i=1}^{m}\left[\rho(X_i - O_i(P)) + (\#(O_i(P)) - \rho(O_i(P)))\right]/\rho(X_i) \quad (10)$$

where P is a segmentation parameter vector, X_i is the union of voxels included by some specialist in the *i-th* segment, X is the set of all segments delimited by the specialists, $O_i(P)$ is the set of voxels belonging to the segment with the largest intersection with X_i among the segments produced by using P as parameter values of the segmentation algorithm, $\rho(J)$ is the sum of weights associated to voxels of the set J, '#( )' is the cardinality function and m is the number of segments in the set X.

It is important to point out that X does not need to represent a complete segmentation of the input image, such that every voxel of the image would belong to a segment in X.

B. Object description

A set of features of each object obtained in the segmentation are computed prior to the classification. They are: average of voxel intensities, compactness, spherical disproportion, sphericity, elongation, Euclidean distance between the center of mass of the object and its slice's center, correlation and energy of co-occurrence matrix generated by the image of 512 gray levels and elements separated by the distances $\Delta x = -5$, $\Delta y = -1$ and $\Delta z = 0$ and correlation and energy of co-occurrence matrix generated by the image of 256 gray levels and elements separated by the distances $\Delta x = -4$, $\Delta y = -4$ and $\Delta z = 0$. Each feature is normalized in range of -1 to 1 before classification.

C. Classification

The final step of nodule detection is the classification of each object into nodule or non-nodule. Many classification techniques may be applied at this step. In the experiments reported in section III a support vector machine (SVM) [6] has been used.

III. EXPERIMENTAL EVALUATION

A. The database

The data set of CT scans were acquired from the public database LIDC consisting of 85 CT scans, stored in DICOM format [9]. The scans were analyzed by four radiologists who may be divergent. To reduce the subjectivity impact on the analysis, just those scans with some object unanimously classified as nodule were used in the experimental evaluation. Besides objects classified differently by radiologists were ignored in the classification phase of this work. For that reason, the present study used 43 scans with 77 nodules (unanimously so classified). Theses scans contain between 101 and 525 slices of 512 x 512 pixels, the average size of voxels is 0,65 x 0,65 x 2 mm and the images are quantized in 16 bits.

B. Nodule detection

The adaptation of segmentation parameters was accomplished in a group of ten scans for this purpose. Thus, to evaluate the nodule detection, the tests were done in the 33 remaining scans (out of 43). In these experiments, the ten scans selected for parameters adaptation were also used as training set for the SVM classifier, and were not included in the test set. Due to the reduced number of available patterns, we used the *leave-one-out* technique in the evaluation.

Figure 2 shows an example of segmentation result. This figure contains a three-dimensional visualization of a nodule with different delimitations, as delimited by four specialists and by the proposed method. Although the main objective of this study is nodule detection rather than accurate nodule segmentation, it should be noticed that the automatically segmented objects are visually close to the reference provided by the specialists.

Table I contains the performance scores collected in our experiments. Alternative segmentation procedures have been considered. The performance is expressed henceforth in terms of sensibility (S) and false positive per slice (FP/slice). The first experiment applied the Otsu's algorithm. The remaining experiments used the proposed methodology. In the experiments 2, 3 and 4, just one criterion (feature) was used for segmentation, while in the experiments 5 and 6 were used two criterions and in the experiment 5 all three criterions

were used.

The performances obtained by Otsu's method as well as by our method with just one criterion are significantly below the performance achieved by our method when two and three criterions are used. In addition, the experiment with three criterions was better than the ones with two criterions. The proposed method with three features achieved in our experiments a sensitivity of 80.9% with 0.23 *FP*/slice. This indicates that the use of multiple criterions to build up heterogeneity measure may improve nodule detection. Moreover the results suggest that detection performance may even grow by increasing more criterions.

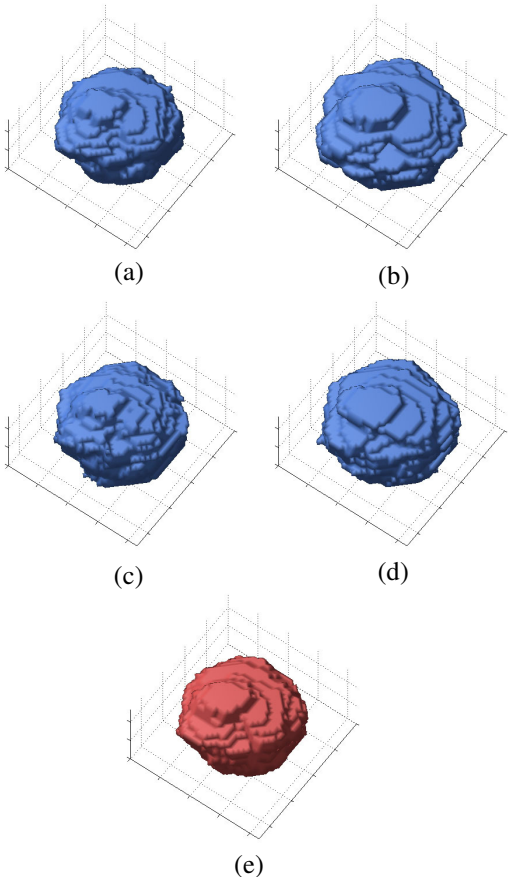

Figure 2. Views of distinct delimitations of one nodule. (a)(b)(c)(d) each one segmented by different physicians. (e) segmented automatically by the proposed technique.

TABLE I. RESULTS OF LUNG NODULE DETECTION

Exp	Segmentation	S (%)	FP/slice
1	Otsu	68,4	0,41
2	variance	67,8	0,40
3	elongation	50,6	0,59
4	spherical disproportion	53,6	0,62
5	variance and elongation	74,3	0,32
6	variance and spherical disproportion	74,8	0,30
7	variance, elongation and spherical disproportion	80,9	0,23

IV. FINAL COMMENTS

This work proposed and evaluated a new methodology for lung nodule detection in computerized tomography images. The novelty resides in taking into account in the heterogeneity metric features that well separate the interest objects from remaining objects present in the image. Genetic algorithms were used to turn the parameters values for segmentation.

The experiments were accomplished on a public database LIDC. The segmentation criterions were automatically selected by the feature forward selection method.

The experimental results have shown that the multicriterion segmentation may significantly improve the nodule detection performance in CT scans. Aspects such as the inclusion/selection of other features in the homogeneity criterion are worth investigating in the continuation of this research.

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