A Fuzzy Approach to Chest Radiography Segmentation involving Spatial Relations

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ABSTRACT
In this paper, we present an approach where we integrate spatial relations in the process of segmentation of chest radiography. In the proposed approach, spatial relations are represented as fuzzy subsets of the image space. Using this strategy, we imitate the reasoning of a physician when interpreting a medical image. The results demonstrate that the introduction of spatial relations can improve the recognition and segmentation of structures with low contrast and ill-defined boundaries.

Keywords
Segmentation, Chest radiography, Spatial relations, Fuzzy sets

1. INTRODUCTION
By 2020, four of the seven major killers worldwide are expected to be lung diseases [1]. Chest radiography has defended its position in the diagnostic workflow despite dramatic advances in the field of computed tomography (CT). The main arguments in favor of chest radiography are broad availability, cost effectiveness as well as the relatively low-dose exposure. However, compared to CT imaging, sensitivity and specificity for the detection of lung nodules are low [2]. Most of the radiographs are chest images [3]. Indeed, chest radiograph is a very popular diagnostic modality, and it provides sufficient pathological information about cardiac size, pneumonia-shadow, and mass-lesions, with low cost and high reproducibility [4].

As computer-aided diagnosis in chest radiography becomes the focus of many investigators, different methods have been developed to obtain automatic lung segmentation [5]. Automatic segmentation of the lung fields is virtually mandatory before computer analysis of chest radiographs can take place [4].

In this paper, we propose a segmentation procedure based on spatial relationships between the lung structures. The use of these spatial relationships is motivated by their high robustness and low inter-patient variability, unlike other structure characteristics such as shape or grey-level values. Furthermore, using this strategy, we imitate the reasoning of a physician when interpreting a medical image. The main ingredients in problems related to spatial reasoning include spatial relationships representation, imprecision representation and, fusion of heterogeneous information and decision-making. Fuzzy set theory is of great interest to provide a consistent framework for all these aspects. It allows to represent imprecision of objects, relationships, knowledge and aims, it provides a flexible framework for information fusion as well as powerful tools for reasoning and decision-making. The aim of this paper is to represent an approach for modeling spatial relationships to segment chest radiographies in the fuzzy set framework.

This paper is organized as follows. Section 1 provides an overview on the related research work which has been carried on various techniques for image segmentation. In Section 2, we briefly present computational representations of spatial relations. Section 3 is devoted to the relations taken into account and the proposed framework which is applied to the segmentation of chest radiography. In Section 4, some final results are shown and discussed, and finally, in Section 5, conclusions are presented.

2. RELATED WORKS
A variety of image processing and analysis methodologies has been proposed for the segmentation of plain chest radiographs [6]. Many of them have focused on the segmentation of the lung fields, whereas fewer have focused on the segmentation of the rib cage or other anatomic structures of the chest [4]. When trying to subdivide the literature, we discern three main areas: rule-based reasoning, pixel classification and hybrid scheme.

The first type relies on rule-based systems which offer their designer the freedom to express his knowledge about the problem in any type of rule or processing imaginable.

There are already many approaches that deal with the rule-based reasoning. Typically segmentation is based around thresholding, edge detection and fuzzy rule-based approach. This section highlights some of these approaches.

[3] delineated lung borders using a single threshold determined from the gray-level histogram of a selected region. Gradient analysis was then used to extend the edges. A smoothing procedure yields the final image. [7] used a combination of gray-level thresholding (both global and local) and contour smoothing.

[8] presented a system to extract lung edges that employs reasoning mechanisms. Instead of using the traditional curve-fitting method to delineate the lung, [5] applied an iterative contour smoothing algorithm to each of the four detected boundary segments (costal, mediastinal, lung apex, and hemidiaphragm edges) to form a smooth lung boundary.

The fuzzy-logic approach, that is less crisp, can offer improved performance in the difficult task of chest x-ray segmentation [9]. That's why several approaches have been developed in the past based on fuzzy-logic.

[9] presented an approach to airway-tree detection in CT images based on fuzzy logic.

[10] used a fuzzy reasoning system in segmentation of the lungs in five lobes. A ridgeness measure is applied to the original CT images to enhance the fissure contrast. Then, the fuzzy reasoning system is used in the fissure search.

The second class relies on pixel classification. Segmentation can be treated as a pixel classification problem by calculating a feature vector for each pixel in the input image. Output is the anatomical class the pixel belongs to. According to [11], there are two variants of classifiers: Classifiers are known as supervised methods and Unsupervised methods.

Classifiers are known as *supervised* methods since they require training data that are manually segmented and then used as references for automatically segmenting new data. There are a number of ways in which training data can be applied in classifier methods.

Among these methods are Bayes Classifier, Artificial neural networks, Deformable models and Markov random field models.

Lung segmentation by pixel classification using neural networks has been investigated by [12] and [13].

Deformable model-based methods, such as active shape model (ASM) and active appearance model (AAM), have been successfully applied in lung field segmentation [14].

[15] presented a new deformable model using both population-based and patient-specific shape statistics to segment lung fields from serial chest radiographs. [6] proposed a methodology that involves detection of salient points on the anatomic structures around the lung fields by subsequent application of simple intensity and edge feature extraction techniques. The salient points detected, are interpolated using Bézier curves smoothly approximating the boundaries of the lung fields.

Markov random field (MRF) modeling itself is not a segmentation method but a statistical model which can be used within supervised segmentation methods.

[16] developed a pixel classifier for the identification of lung regions using Markov random field modeling. An iterative pixel-based classification method related to Markov random fields was presented by [17].

Unsupervised methods essentially perform the same function as classifier methods without the use of training data. In order to compensate for the lack of training data, unsupervised methods iterate between segmenting the image and characterizing the properties of the each class. In a sense, unsupervised methods train themselves using the available data.

The commonly used unsupervised methods are: Hard C - Means, FCM (Fuzzy C- Means), PCM (Possibilist C-Means), Graph cuts algorithm.

Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. This method (developed by [18] and improved by [19] is frequently used in pattern recognition.

Recently, many researchers have brought forward new methods to improve the FCM algorithm [20].

[21] presented a Gaussian kernel-based fuzzy clustering algorithm with spatial constraints for automatic segmentation of lung field in chest radiographs.

[20] presented an image segmentation approach using Modified Fuzzy C-Means (FCM) algorithm and Fuzzy Possibilistic c-means algorithm (FPCM). This approach is a generalized version of standard Fuzzy C-Means Clustering (FCM) algorithm.

Hybrid methods were formulated by combining rule-based methods and pixel-based classifications for lung field segmentation [22].

The review in the precedent section shows that the problem of lung segmentation was limited on the extraction of lung boundaries. However, the lungs in their nature are segmented into five lobes and because pulmonary disease is usually not uniformly distributed in the lungs, it is useful to study the lungs on a lobe-by-lobe basis. Thus, it is important to segment not only the lungs, but the lobes as well [10].

Many studies have been concerned with the segmentation of lung lobes but in CT images because the fissures that segment the lungs are visible in this modality. On the contrary of the CT image, superimposed anatomical structures in chest radiography make the fissures that segment the lungs visible only if the patient is perpendicular to the x-ray at the time of taking the image. That's why segmentation based on the detection of fissures is not studied in radiographies. The lobes of the lung are further divided into segments which physicians based on to define in which lobe the lesion is localized when they use chest radiographies (see Figure 1). But these segments have similar intensities and their boundaries are poorly defined.

Physicians can quickly judge the site of lesion in the lung, for example, "*lesion* is in the right apical" that's mean that the lesion is localized in the right upper lobe. But this has turned out to be a rather elusive task for automation for many reasons such as the positioning of the patient that's differing from the standard in many cases as presented in Figure 2. Even the idea to base on the detection vertebrae to locate segments of the lungs is not evident because it is unable to locate the internal structures like the parahilar.

As well a question that arose: how the physicians can differentiate between these segments? Looking at the chest radiography, it seems clear that these structures have similar intensity and poorly defined borders. Though, physicians can locate segments with a simple look.

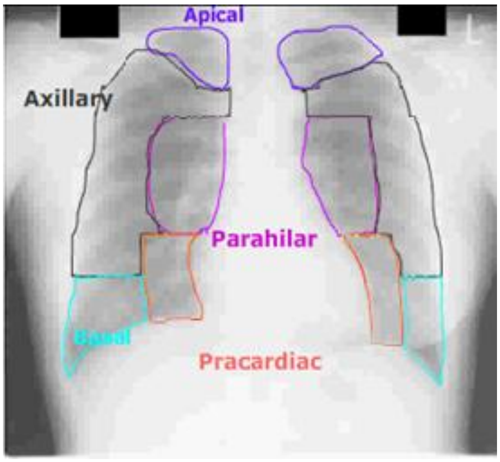


Figure 1: Segments of lungs

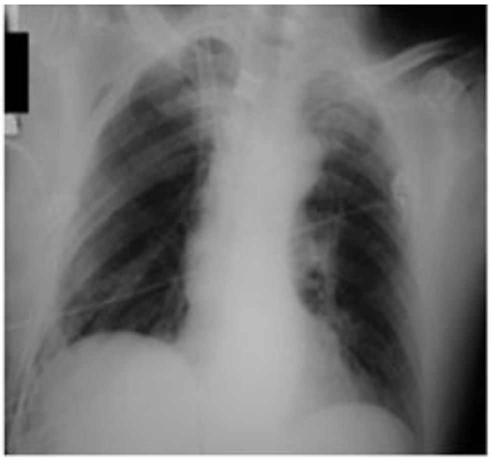


Figure 2: Chest radiography that's differing from the standard

Spatial relations could be of great help to find the contours of poorly contrasted objects, with ill-defined boundaries or sharing similar intensities with their neighbors [23]. These relations are usually classified into different types including topological, distance and directional relations [24].
Their ability to provide structural knowledge makes them potentially useful for a wide range of imaging applications including medical imaging. The segmentation of chest radiography is a typical example of imaging application in which spatial relations can be useful.
In this paper, we propose an approach which aims at integrating explicitly spatial relations in the segmentation process. This should allow to model more directly expert knowledge expressed as linguistic descriptions and to explicitly choose the constraints which will be included in the segmentation.

3. SPATIAL RELATIONS

To use spatial relationships in a segmentation procedure, two preliminary steps are required. First, we must break the image into a set of spatial entities linked by relationships. The second step concerns the representation of spatial relationships.
We have developed a description of lung structures from the spatial relationships between them. The description is given by service of medical imaging of CHU Charles Nicole.
We consider spatial relations that define the position of a target object with respect to a reference object. To illustrate our purpose, let us provide some examples of spatial relations between lung structures:
• The left (respectively, right) apical is *above* and *adjacent of* the left axillary;
• The left (respectively, right) parahilar is adjacent and on the right of the left (resp. right) axillary.
• The left (respectively, right) paracardiac is below and adjacent of the left (resp. right) parahilar.
In the two first examples, the apical and the parahilar are target objects and their position is defined with respect to the axillary, which is chosen as reference object. In the third example, the parahilar becomes a reference object.
It is first necessary to provide a computational representation of the relations. Approaches for representing spatial relations can be divided into qualitative and quantitative methods [23]. The first ones often rely on formal logic. The quantitative methods provide a numerical evaluation of the relations. An additional distinction can be made between quantitative methods: a first type of approach evaluates spatial relations between two given objects; a second type defines the satisfaction of a relation, with respect to a given reference object, at each point of the space. We make use of the second type of approach in which spatial relationships are represented as fuzzy subsets of the image space. In the present work, directions and adjacencies are taken into account. They must be modeled as spatial fuzzy sets. We choose fuzzy logic theory to solve the complex problem of segmenting lungs in x-ray images because fuzzy sets provide a common framework to represent different types of individual spatial relations [23]. Fuzzy logic is finding applications that range from process control to medical diagnosis [25]. Moreover, fuzzy logic theory provides a powerful decision making tool for medical image analysis by its ability to address uncertainties using overlapping fuzzy sets [9].
Besides, the relations can be easily combined using fuzzy fusion operators [26]. The fuzzy set framework has been used to represent different types of spatial relations including adjacencies, distances, directions [27] and symmetries [28]. Keller and Wang [29] used spatial relations to automatically generate linguistic descriptions of images. A system for describing and modeling the relative positioning of handwritten patterns based on directional relations has been proposed by [30]. [23] have proposed to use fuzzy spatial relations for brain structure segmentation on MRI. [31] proposed a fuzzy ontology of spatial relations, in order to guide image interpretation and the recognition of the structures.

3.1. Fuzzy representations of spatial relations: some preliminaries

Representation of objects by spatial fuzzy sets: A spatial fuzzy set is a fuzzy set defined on the image space, denoted by $\mathcal{S}$, $\mathcal{S}$ being typically $\mathbb{Z}^2$ *or* $\mathbb{Z}^3$ or for 2D or 3D images. Its membership functions μ (defined from $\mathcal{S}$ into [0,1]) represents the imprecision on the spatial definition of the object (its position, size, shape, boundaries, etc.). For each point x of $\mathcal{S}$ (pixel or voxel in digital 2D or 3D images), $\mu(x)$ represents the degree to which x belongs to the fuzzy object.

3.2. Reference system

Making spatial relations explicit, in particular metric relations, requires a reference system. Let us consider the example of the directional relation "**x** *in the right of* **y**''. The semantics of the relation is not the same depending on whether the reference system is object **y** itself or an external observer. In order to define a binary relation between two objects, at least the three following concepts have to be specified: the target object, the reference object, and the reference system. In general, a reference system is categorized either from the observer's point of view (which can be relative or absolute), or according to the way the relation is used (intrinsic, extrinsic, or deictic use). It is therefore important to define the reference system associated to the relation.

3.3. Directional relations

Directional relations, which are useful to describe the relative position of an object with respect to other ones, require the space to be oriented, i.e. a reference system, as described below. The most used relations are related to two axes of References (For 2D image): "To the right of'', "To the left of'', "Above'', "Below''.
Directional relations are represented using a morphological approach [32].

3.3.1. Morphological approach

A morphological approach has been proposed in order to evaluate the degree to which an object A is in some direction with respect to a reference object *R*, consisting of two steps:

- A fuzzy landscape is defined around the reference object *R* as a fuzzy set such that the membership value of each point corresponds to the degree of satisfaction of the spatial relation under examination. It is resulted from the operation of morphological dilation applied on the reference by means of a fuzzy structuring element defined on *S* as

$$\forall\, P \in S, V\alpha(P) = \max\left(0{,}1 - \frac{2}{\pi} arccos \frac{\overrightarrow{OP}\ \cdot\ \overrightarrow{u\alpha}}{\overrightarrow{OP}}\right) \quad (1)$$

Where O is the center of the structuring element and u_α a unit vector corresponding to the direction α the membership function ν associate for every point of space a value between 0 and 1, which vary with the angle between $\underset{OP}{\rightarrow}$ and the direction under consideration α.

For a given reference object *R* positioned in the space *S*, the landscape μ is constructed by operating a morphologic dilation of *R* by means the structuring element:

$$\forall\, P \,\epsilon\, S, \mu(R)(P) = \max_{Q \in R} \nu(P-Q) \quad (2)$$

The figure 3 represents semantics of directional relations for four main directions, represented as fuzzy sets on the angle space according to the morphological approach.

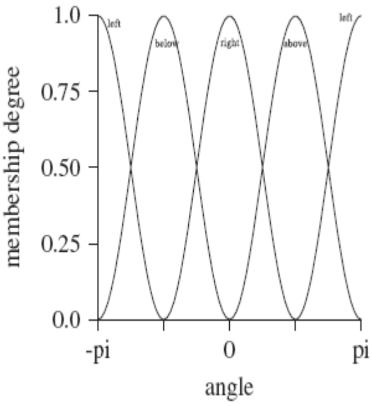


Figure 3: Semantics of directional relations for four main directions, represented as fuzzy sets on the angle space [31]

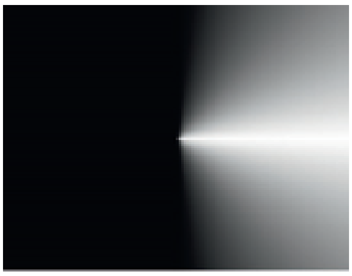


Figure 4: Fuzzy structuring element ν representing the semantics of "to the right of'' in the spatial domain derived from Fig 3 [31]

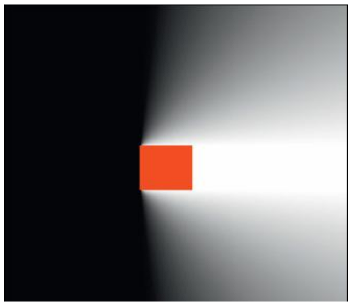


Figure 5: Fuzzy dilation of object R (the square) by the fuzzy structuring element ν [31]

- Then the object *A* is compared to the fuzzy landscape in order to evaluate how well the object matches with the areas that are in the desired direction. This is done using a fuzzy pattern matching approach [32] which provides an evaluation as two numbers: a necessity degree *N* (3) (a pessimistic evaluation) defined as a degree of inclusion and a possibility degree Π (4) (an optimistic evaluation) defined as a degree of intersection. An average measure can also be useful (5) [32].

$$N^R\,(A) = \inf_{P \in A} \mu(R)(P) \quad (3)$$

$$\Pi^R(A) = \sup_{P \in A} \mu(R)(P) \quad (4)$$

$$M^R\,(A) = \frac{1}{|A|} \sum_{P \epsilon A} \mu(R)\,(P) \quad (5)$$

3.4. Topological relations

In this section, we consider the important topological relation of adjacency presented in [27].

The definition for fuzzy adjacency between μ and ν (9) involves a degree of intersection $\mu_{int}(\mu,\nu)$between two fuzzy sets μ and ν defined on $\mathcal{S}$ (6), as well as a degree of non-intersection $\mu_{\neg int}(\mu,\nu)$(7), and a degree of neighborhood n_{xy}between two points *x* and *y* of $\mathcal{S}$ (8).

$$\mu_{int}(\mu,\nu) = \sup_{x \in \mathcal{S}} t[\mu(x),\nu(x)] \quad (6)$$

Where t is any t-norm.

$$\mu_{\neg int}(\mu,\nu) = c[\mu_{int}(\mu,\nu)] \quad (7)$$

Where c is a fuzzy complementation (for instance defined as

$$\forall a \in [0{,}1], c(a) = (1-a)$$

$$n_{xy} = \frac{1}{1+d_{\mathcal{S}}(x,y)}, or\ n_{xy} = \frac{1+exp(-b)}{1+\exp b\left(\frac{d_{\mathcal{S}}(x,y)-1}{S}-1\right)} \quad (8)$$

Where $d_{\mathcal{S}}$ denotes the Euclidean distance in $\mathcal{S}$ and b and S are two positive parameters which control the shape of the curve.

$$\mu_{adj}(\mu,\nu) = t\left[\mu_{\neg int}(\mu,\nu), \sup_{x \in \mathcal{S}} \sup_{y \in \mathcal{S}} t[\mu(x),\nu(y),n_{xy}]\right] \quad (9)$$

4. GLOBAL APPROACH

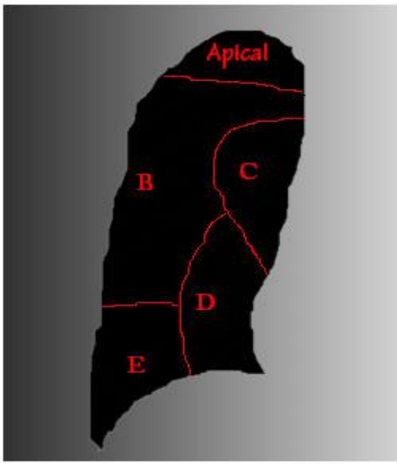


Figure 6 : The segments of the right lung. B, C, D, E are the searched objects. B: the axillary, C: the parahilar, D: the paracardiac, E: the basal

Figure 7 : The search space of the object "axillary'' corresponds to the spatial relations "to the below of the apical''

Table 1: Evaluation of the relation

Measure	Value
$M^R(A)$	0,97
$N^R(A)$	0
$\Pi^R(A)$	1

Our approach combines segmentation and recognition of lung segments using spatial relations. Let us detail the process in the case of Figure 6.

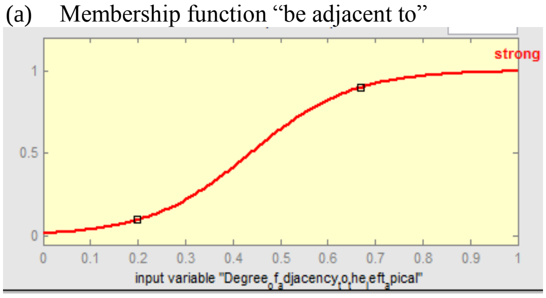
- **Segmentation and labeling:** We are interested in finding the directional and adjacency spatial relations between lung structures where A represents the apical and B–E the four regions to be labeled.
- **Calculation of spatial relationships between different components:** We are based on the average measure to evaluate how well the object B matches with the areas that are in the desired direction and the degree of adjacency of the two objects A (the apical) and B. These two values are the inputs of our fuzzy system.

  Fuzzy rule system: Fuzzy logic systems base their decisions on inputs in the form of linguistic variables derived from membership functions which are formulas used to determine the fuzzy set to which a value belongs and the degree of membership in that set. The variables are then matched with the preconditions of linguistic IF-THEN rules, and the response of each rule is obtained through fuzzy implication [33]. In this work, 8 fuzzy rules are used.

1. **IF** *the object B is below* **AND** *adjacent to the right apical (respectively, the left)* **THEN** *B is the axillary*.
2. **IF** *the object C is below the apical* **AND** *on the right (resp.left) and adjacent to the axillary* **THEN** *C is the parahilar*.
3. **IF** *the object D is below and adjacent to the parahilar* **AND** on the *right (resp.left) and adjacent to the axillary* **THEN** *D is the paracardiac*.
4. **IF** *the object E is below and adjacent to the axillary* **AND** *on the left (resp.right) and adjacent to the paracardiac* **THEN** *D is the Basal.*

To perform compositional rule of inference, the response of each rule is weighted according to the confidence or degree of membership of its inputs, and the centroid of the responses is calculated to generate the appropriate output [33]. The memberships of the two inputs illustrated by Figure 8.

(a) Membership function "be adjacent to"



(b) Membership function "be on the direction of"

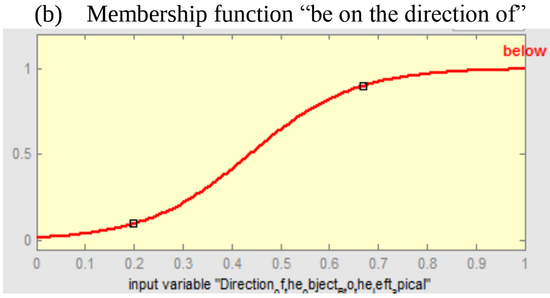


Figure 8 : (a) The membership of the first input E1 **(b) the membership of the second input E2**

The change in the membership values can improve the accuracy of the output.

- **Output of linguistic description:** Since the system attempts to model the reasoning process of a human expert, the output describes the searched object.

The entire of the modeled system is presented in figure 9.

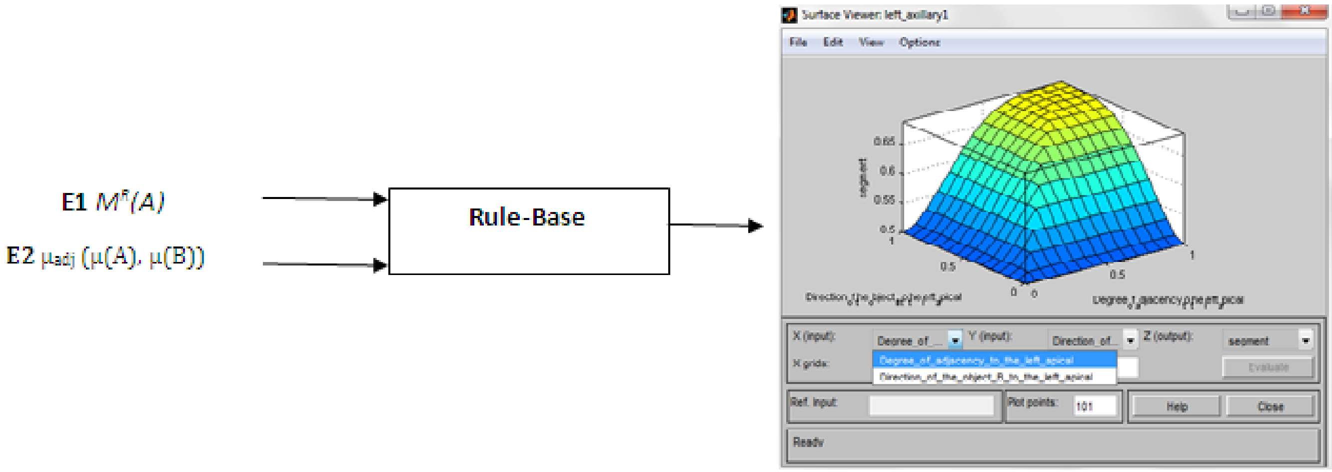


Figure 9: Design of our fuzzy system

5. EXPREMENTS AND RESULTS

5.1. Image data

The chest radiographs are taken from the JSRT database [14]. This is a publicly available database with 247 PA chest radiographs collected from 13 institutions in Japan and one in the United States. The images were scanned from films to a size of 2048 X 2048 pixels, a spatial resolution of 0.175 mm/ pixel and 12 bit gray levels. 154 images contain exactly one pulmonary lung nodule each; the other 93 images contain no lung nodules. In order to test our approach, the chest radiographs require separation of lung fields from background. We prepare manually lung field masks (see Figure 10).

(a) (b)

Figure 10: (a) Original x-ray image JPCLN001 (b) manually segmented lung fields mask

5.2. Results and discussion

We judge the performance of our segmentation approach using several evaluation criteria often used in the literature (see Table 2). For a ten class segmentation problem, one can distinguish true positive (TP) (labeled pixels correctly detected), false positive (FP) (non-labeled pixels detected as labeled), false negative (FN) (pixels of labeling not detected), and true negative (TN) (pixels of non-labeling correctly detected). From these values, measures such as accuracy, sensitivity, specificity and overlap can be computed given by the following equations.

$$SE = \frac{TP}{TP+FN} \quad (10)$$

Sensitivity (SE): It corresponds to the proportion of true positives relative to all structures that should be segmented. Sensitivity tends to 1 (resp.0) if there is little (resp. many) false negatives. This indicator allows evaluating to what extent the entire of a searched structure is segmented.

$$SP = \frac{TN}{TN+FP} \quad (11)$$

Specificity (SP): It corresponds to the proportion of true negatives relative to all structures that should be segmented. Specificity tends to 1 (resp.0) if there is little (resp. many) false positives. This indicator allows evaluating to what extent the entire of the complement of a desired structure is not segmented.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (12)$$

Accuracy: the accuracy is the proportion of true results (both true positives and true negatives). An example of a successful segmented image is illustrated by Figure 11.

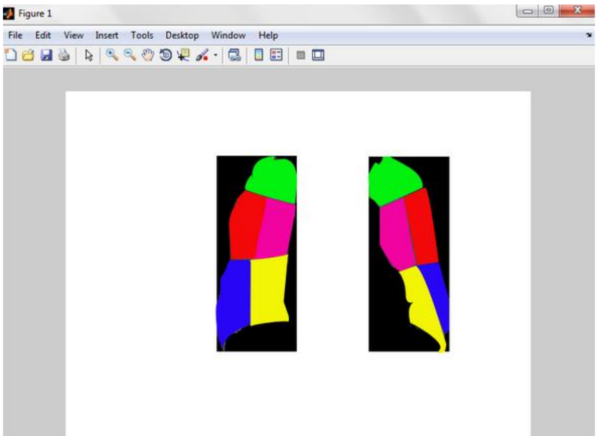


Figure 11: Successful segmented image

Table 2: Quantitative results for images

Image	Segment	SE	SP	Accuracy
JPCLN001	Left_Axillary	85,4	90,1	87,2
	Right_Axillary	82 ,8	88,3	85,5
	Left_Parahilar	86,2	87,5	86,7
	Right_parahilar	85 ,3	88,1	87,3
	Left_Paracardiac	70,1	67,8	70,0
	Right_Paracardiac	89,9	86,2	86,6
	Left_Basal	81,7	83,8	82,1
	Right_Basal	82,7	81,5	80,5
Average result on all images of JSRT database	Left_Axillary	84,0	82,2	82,1
	Right_Axillary	86 ,8	85,5	85,2
	Left_Parahilar	85,7	83,2	84,4
	Right_parahilar	84 ,9	81,1	82,8
	Left_Paracardiac	72,4	65,5	68,8
	Right_Paracardiac	87,6	86,7	86,5
	Left_Basal	81,7	82,8	81,5
	Right_Basal	82,7	81,5	81,7

Results show that this method outperformed greatly with a good accuracy almost for all lung structures as expected. The recognition rate for the left paracardiac is low compared with the other structures. Indeed, the left paracardiac is behind the heart and many pixels are omitted. Since most of studies in literature have not addressed the problem of the specification of different segments of the lungs in the radiographic image, we cannot compare our result with them.

6. CONCLUSION

An automatic chest radiography segmentation framework with integration of spatial relations has been proposed in this work. Spatial relations are represented using fuzzy subsets of the 2D space. In the present work, we used directional and adjacencies relations. The validation results show that the automatic method can segment lung close to those defined by manual tracings. The agreement between the automatic and manual chest radiography segmentations is strong. The results of lung segmentation can be used directly for lung nodule detection and mainly for classification since we can deduce the nature of the lesion from its site. For example the lung infection is usually localized in the apical.

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