Mathematical Morphology and Active Contour Model: A Cooperative Approach for Segmentation of Lung Contours in CT

Françoise PRETEUX*, **Y. HEL-OR***,+

* **Département IMAGES, 46 rue Barrault, 75013 Paris, France**
+ **Department of Computer Science, The Hebrew University, Jerusalem, Israel**

ABSTRACT

We propose an energy formulation for solving the problem of lung contour detection based on mathematical morphology (MM) and active contour model. The novelty of our contribution is to express the external energy functional as a combination of conditional-gradient and anatomical a priori knowledge expressed in terms of distance functions. The aspect of sensitivity to the initialization step is overcome by combining expanding and shrinking deformation processes. It results in an automatic and parameter-independent algorithm yielding the lungs' contours under either of three following complex cases : (1) over-inflated, (2) close together or (3) with hyper-attenuated areas located close to the peripheral pleura.

INTRODUCTION

The concept of energy is fundamental in image processing and pattern recognition. Description and characterization of a segmentation or texture analysis problem may be modeled in terms of energy. The modeling is either global (Gibbs distribution) or local (conditional probabilities) and it correspond to a distance information (enclidean, topographical or differential distance), a field of deformation (active contour) or a motion (temporal sequence).

In our previous research concerning the detection and recognition of bronchopulmonary lesions in computerized tomography (CT), we have successfuly applied one such energy approach. The hypo-attenuated areas, mainly due to emphysema, have been detected by defining a deterministic energy based on a density criterion (1). The hyper-attenuated areas such as micronodules, nodules, masses, however, have been recognized by introducing non-stationary local energy components in a Markovian model (2), (3).

Nevertheless, reliable and accurate quantification of clinical parameters such as the rate of abnormal parenchyma, the 2d or 3d topography of the pulmonary lesions and the efficient right and left lung volumes which are of a great importance for radiologists, requires an automatic procedure of the detection of lungs' contours. Because of the great variability in size, shape, location and density of the lesions, this is a very difficult boundary segmentation problem especially in the cases of CT examinations of patients suffering from chronic infiltrative lung diseases.

In this paper, we propose an energy formulation for solving the problem of lung contour detection based on mathematical morphology (MM) and active contour model. The novelty of our contribution is to express the external energy functional as a combination of conditional-gradient and anatomical a priori knowledge expressed in terms of distance functions. The aspect of sensitivity to the initialization step is overcome by combining expanding and shrinking deformation processes. It results in an automatic and parameter-independent algorithm yielding the lungs' contours under either of three following complex cases : (1) over-inflated, (2) close together or (3) with hyper-attenuated areas located close to the peripheral pleura.

In Section 1, we briefly describe the medical framework, the previous

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research and the boundary segmentation problem we have in hand. Section 2 deals with the fundamental principles of active contour models. This is followed by Section 3 presenting in detail the developed model associated with the lungs' contours. Finally, in Section 4, efficiency and robustness of the proposed algorithm are discussed.

1- THE PROBLEM OF THE LUNGS' CONTOURS SEGMENTATION

Our data set consists of the CT examinations of 15 patients suffering from diffuse infiltrative lung diseases. For each patient, we have a series of about 30 slices, each 1.5 mm in thickness, with 10 mm between two consecutive slices and in 512x512 reconstruction matrices.

Radiologically, the normal lungs appear as pulmonary interstitium with low densities, containing vasculary elements with middle and high densities and aeric elements with very low densities. They are surrounded by ribs with very high densities.

The lesions due to the active and reversible phase of the infiltrative pneumopathies (sarcoidosis, lymphangiomatosis) alter the pulmonary texture which is replaced by hyper-attenuated areas (with high densities) corresponding to micronodules, nodules, and masses (fig. 1a).

In our previous research, we have developed an automatic procedure for segmenting the normal lungs on any CT slice (4). This region segmentation approach is based on MM and, more precisely, on the concepts of connection cost and topographical propagation (5). This allows to take into account the 3d topology of the CT image and to model the lungs' contours as a watershed with respect to the topographical distance (6). The right and left pulmonary masks obtained perfectly match the parenchyma except for the hyper-attenuated areas exclusively located close to the peripheral pleura (the internal ones being well-segmented) (fig. 1b). Because the missing contours are convex and close to the ribs, we have attemped to perform a region growing from the previous binary masks depending on the distance function relative to the ribs. This improves the result of the segmentation but overestimates the parenchyma without taking into account the natural smooth shape of the lungs. In order to define perfectly the lungs' contours, we adopt an energy approach based on an active contour model.

2- ACTIVE CONTOUR MODEL : FUNDAMENTAL PRINCIPLES

Let E_2 be an Euclidean bidimensional space. Let $\mathcal{C}(E_2)$ denote the set of $\mathcal{C}^2$-continuous closed curves of E_2 and $\mathcal{D}(E_2,\mathbb{R})$ be the set of twice differentiable mappings from E_2 to $\mathbb{R}$. **A deformable contour** is defined by (C, E_{int}) where $C \in \mathcal{C}(E_2)$ and E_{int} denotes the internal energy functional on $\mathcal{C}(E_2)$ modeling the mechanical properties of C.

Let E_{ext} be an external energy functional defined on $\mathcal{C}(E_2)\times\mathcal{D}(E_2,\mathbb{R})$. An **active contour** is defined by the triplet (C, f, E_{tot}) where $C \in \mathcal{C}(E_2)$, $f \in \mathcal{D}(E_2,\mathbb{R})$ and E_{tot} denotes the total energy functional on $\mathcal{C}(E_2)\times\mathcal{D}(E_2,\mathbb{R})$ such that :

$$\forall\ C \in \mathcal{C}(E_2),\ \forall\ f \in \mathcal{D}(E_2,\mathbb{R}) \quad E_{tot}(C,f) = E_{int}(C) + \lambda E_{ext}(C,f).$$

Under certain conditions (7), the real coefficient λ appears as the inverse of a regularization parameter (8). It controls the degree of interaction between the deformable contour defined by E_{int} and the image associated with E_{ext}.

Given an active contour (C_0, f, E_{tot}), a **deformable process** of C_0 is a sequence $(C_u)_{u\in\mathbb{R}^+}$ of $\mathscr{C}(E_2)$ so that $C_{u=0} = C_0$ and the sequence $(E_{tot}(C_u,f))_{u\in\mathbb{R}^+}$ is continuously decreasing in $\mathbb{R}^+$. A state of equilibrium of the active contour C_0 submitted to the deformation process $(C_u)_{u\in\mathbb{R}^+}$ is the curve $C_\infty \in \mathscr{C}(E_2)$ verifying :

$$E_{tot}(C_\infty,f) = \lim_{u\to\infty} E_{tot}(C_u,f).$$

Obviously, a state of equilibrium of C_0 corresponds to a local minimum of the total energy functional E_{tot}.

Let $X(s) = (x(s), y(s))^t$ be a generic point of C parametrized by the arc-length $s \in [0,1]$ with $X(0) = X(1)$. According to (7,9), the internal energy functional is expressed by :

$$E_{int}(C) = \int_0^1 \alpha(s) \|\partial X/\partial s\|^2 ds + \int_0^1 \beta(s) \|\partial^2 X/\partial s^2\|^2 ds.$$

The two terms defining E_{int} correspond, respectively, to the stretching energy of a menbrane and the bending energy of a thin plate. The functions $\alpha(s)$ and $\beta(s)$ take into account local properties of C .

According to (7,9), the external energy functional E_{ext} tends to attract the active contour onto the high gradient curves located in a vicinity of its initial position C_0. It is expressed by the general formulation :

$$E_{ext}(C,f) = -\int_0^1 \phi((\nabla f(X(s)))^t W(X(s)) (\nabla f(X(s)) ds$$

where ϕ is a non-negative non-decreasing real mapping of $\mathbb{R}^+$ and $W(X(s))$ a weighting (2×2) real matrix.

Finally, the minimization of E_{tot} is performed according to variational principles. The discretized expressions are the following :

$$Ax = -\frac{\partial E_{ext}}{\partial x} \quad \text{and} \quad Ay = -\frac{\partial E_{ext}}{\partial y}, \qquad (1)$$

where A denotes the pentadiagonal cyclic $(n\times n)$ matrix defined in (9) and $x = (x_1, x_2, ..., x_n)^t$ and $y = (y_1, y_2, ..., y_n)^t$ denote the $(1\times n)$ matrices of positions along the discretized contour.

The matrix A can be very ill-conditioned and lead to very unstable schemes. To guarantee a stable convergence, we assume that the deformation process satisfies the laws of Lagrangian dynamics. Thus, given an initialization C_0, the optimal contour segmentation is defined by the stable equilibrium of the system :

$$\forall\lambda \in \mathbb{R}^+ \quad (A + \gamma I)x = \gamma x - \frac{\partial E_{ext}}{\partial x} \quad \text{and} \quad (A + \gamma I)y = \gamma y - \frac{\partial E_{ext}}{\partial y}. \qquad (2)$$

The discrete iterative scheme is given by :

$$\forall\lambda \in \mathbb{R}^+ \qquad x^{u+1} = (A + \gamma I)^{-1} (\gamma x^u - \frac{\partial E_{ext}(C^u,f)}{\partial x}$$

$$y^{u+1} = (A + \gamma I)^{-1} (\gamma y^u - \frac{\partial E_{ext}(C^u,f)}{\partial y}. \qquad (3)$$

The convergence of this process is achieved only if : $\left|\frac{\gamma}{|A|+\gamma}\right|^n \longrightarrow 0,$

where $|A|$ is the greatest eigenvalue of the matrix A.

Active contour model is fundamentally local and thus suffers from two major problems : undesirable attractions by non-significant localized or regionalized zones in the image and sensitivity to the initialization and to the value of γ.

Let us show how this theoretical framework may be applied to our segmentation problem and how we may overcome the drawbacks inherent to one such boundary segmentation approach by introducing a priori knowledge expressed by MM operators.

3- THE DEVELOPED MODELING

From a practical point of view, an active contour is characterized by the initial active contour, the external energy functional and the values of the different parameters (α, β and λ). All this information is deduced from a priori knowledge of the images and the contour segmentation problem in hand.

In our case, the a priori knowledge consists of :

1- binary masks matching the normal right and left parenchyma and resulting from the MM approach (Section 1),

2- convexity and regularity of the external pleura,

3- anatomical information, especially concerning the relative configuration between ribs, soft tissues and peripheral pleura.

The second point ensures that we may set : $\forall$ s $\in$ [0,1] $\alpha(s) = \alpha$ and $\beta(s) = \beta$.
The third point guarantees that the contours we are looking for are close to the ribs and are always located in the interior of the curve linking the internal side of the ribs. Thus, ribs play a strategic role in the proposed model which combines expanding and shrinking deformation processes. The first step corresponds to a global expansion of the initial active contour located inside the lung to be segmented. From the resulting equilibrium state, a globally shrinking deformation process is performed. This strategy allows to overcome the problem of sensitivity to the initialization.

3-1 The expanding active contour model

The initialization step is given by a small circle centered inside the binary mask of the lung (fig. 2b). The external energy functional (fig. 2a) is defined by :

- an expanding force which is equal to the weighted Euclidean distance relative to the centroide of the binary pulmonary mask,
- infinite values in the place of the ribs and the skeleton by influence zones (SKIZ) of the two binary lung masks (or simply the vertical line separating them).

The peaks and the ridge associated, respectively, with the ribs and the SKIZ prevent an expansion to infinity. They play the role of barricades : when the internal side of the ribs is reached, the contour stretches only around. At the end of the expanding process, we have obtained all the information to be integrated in the final shrinking process :

- the initialization contour slightly overflowing the lung (fig. 2c),
- markers of the internal sides of the ribs (by intersecting the ribs with the contour).

3-2 The shrinking active contour model

The shrinking deformation process is performed (until convergence (fig.3c)) according to an external energy functional which takes into account conditional gradient information (10) (fig. 3a) and information provided by the ribs (fig. 3b). It is expressed as follows :

$$E_{ext} = \psi(f).(\nabla GI)(f) + \nu \exp(-d/\mu),$$

where $\psi(f)$ denotes the anamorphosis of f providing an encoding of the CT image according to absolute density criteria and G denotes the DOG operator. Here, ν and μ are respectively the ribs influence and the attenuation coefficient and d denotes the Euclidean distance relative to the ribs.

The iterative process stops when a local minimum energy of E_{tot} is reached. If we assume that, at the minimum energy, the process is stationary, the stopping criterion should be the following :

$$\Delta X = |X^{u+1} - X^{u}|^2 < \varepsilon \qquad (\text{for } \varepsilon > 0).$$

However, by applying this criterion, close to the minimum, ΔX increases instead of to decrease and oscillations arise when we are close to the minimum point of the energy. In (11), the proposed solution solving this problem is to fit the parameter γ during the process adaptatively so that $|\partial X/\partial u|$ remains equal to a given value ΔX. The parameter γ is then determined by : $\gamma = |\partial E_{tot}/\partial X| \;/\; \Delta X$. Because this solution is time-consuming, we simply adopte an heuristic solution : at each iteration, the total energy functional is calculated. If during the last K iterations the energy did not decrease, then the process stops and the last best solution is kept (the Kth iteration before the end). Finally, we set $\gamma = 0.2$ and $K = 7$. The parameters α, β, λ, ν, and μ have been fixed from a training data set.

4- RESULTS AND DISCUSSION

Efficiency and robustness of the automatic and parameter independent proposed algorithm have been established on a collection of 70 CT images, good prototypes of the worst possible configurations : lungs over-inflated or close together and including hyper-attenuated areas of variable size near the peripheral pleura. The Detected contours perfectly coincide with those estimated by expert radiologists especially for CT images for which ribs are regularly distributed. Nevertheless, since the expanding force based on the distribution of the ribs depends on the distance between them, results may be less satisfying for the first few slices of the series where ribs are sparsely distributed and lungs have no regular shape.

CONCLUSION

We have presented a reliable and accurate method based on mathematical morphology and active contour model for detecting the lungs' contours in CT images. Our novel contribution is to combine expanding and shrinking deformation processes. Moreover, the external energy functional is deduced from a priori knowledge on the one hand and image processing previously performed on the other hand. In addition, our approach results in an accurate and entirely automatic initialization as well as precisely defined stopping criterion - two important problems in active contour model. This method, general in its principle, may be easily extended to segment dynamic or volumic data.

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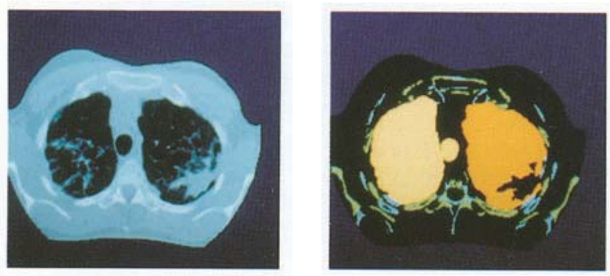

Fig. 1 : Morphological segmentation.
1a : Initial CT image.
1b : Lung masks : hyper-attenuated areas are not segmented.

Fig. 2 : Expanding deformation process.
2a : External energy. 2b : Initialization step. 2c : Final contour.

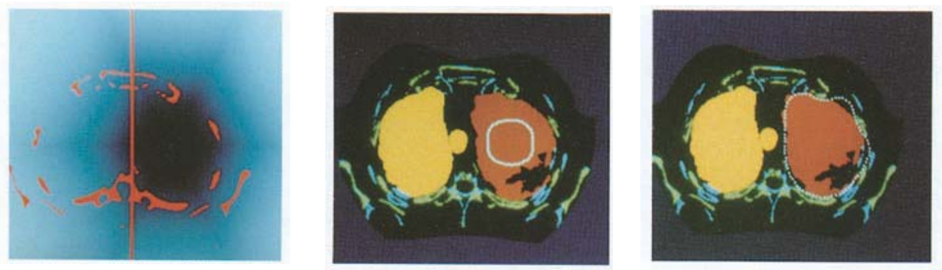

Fig. 3 : Shrinking deformation process.
3a : Distance to the ribs. 3b : Conditional gradient. 3c : Final lung contour.