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Region-based snake with edge constraint for segmentation of lymph nodes on CT images

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ABSTRACT

Lymph nodes segmentation is a tedious process with large inter-user variability when performed manually. To facilitate lymph nodes assessment for lung cancer patient, we present an automatic and improved snake segmentation method for thoracic lymph nodes on CT images in this paper. We first investigated the performance of both edge-based and region-based snake algorithms for the segmentation task, using a *B*-spline contour parameterization. The effect of the number of *B*-spline control points on the snake performance was also examined. Both edge-based and region-based snakes were found to have their own advantages and disadvantages for lymph nodes segmentation. We further developed a method of region-based snake with edge constraint, which utilizes a self-adjusting mechanism to integrate both edge and region information in a constructive manner. The average Dice Similarity Coefficient obtained was 0.853 ± 0.059 and 0.841 ± 0.108 for the baseline and follow-up lymph nodes respectively using the proposed method. The method was found to be an effective lymph node segmentation method and would potentially be useful to help with treatment response evaluations in the clinical practice.

1. Introduction

Lymph nodes assessment is important in clinical practice and drug trials as changes in lymph nodes often indicators of disease progression. In the newly revised RECIST 1.1 [1], uni-dimensional measurement in short axis of enlarged lymph nodes is required for treatment evaluation of cancer patient. Two dimensional (2D) measurement, which takes area into account, could be more revealing on the actual size of the structure. This requires segmentation of the lymph nodes in medical images such as computed tomography (CT) scans. However, manual segmentation is a very tedious process, which suffers from low reproducibility. Computer-aided lymph nodes segmentation tool could be valuable in the clinical practice. Nevertheless, automatic segmentation of lymph nodes is a very challenging problem. First, lymph nodes are very small structures whose boundaries can be obscured due to partial volume effect. Second, they often appear in various size and shape (from bean shape to circular shape and other irregular shapes). Third, they can be located adjacent to structures of similar intensity range, making threshold-based segmentation methods ineffective. Some lymph nodes even share part of the boundary with surrounding tissues. Fourth, high contrast structures such as blood vessels, which have prominent edge profiles, could suppress the expression of lymph node edges and potentially mislead model-driven algorithms based on edge information. Last but not least, central necrosis can occur and further disturb the interior homogeneity of the structure.

Several methods have been proposed to assist study of lymph nodes in CT scans in a semi-automatic or automatic manner. Rogowska et al. [2] in 1997 were the first to evaluate four elementary techniques for lymph nodes segmentation on CT images, namely manual tracing, semi-automatic local criteria threshold selection, Sobel/watershed technique, and interactive deformable contour algorithm. Results from phantom images showed that reliable lymph node segmentation is only possible with the use of model-based knowledge. Honea et al. [3] applied the original parametric snake model on phantom nodes and achieved promising segmentation results using information on both the shape of the object and its image properties in the energy formulation. Honea and Snyder [4] extended the 2D active contour model into three-dimensional active surface model. By deriving surface energy from 3D data and incorporating a balloon force, a single user-chosen point balloon will inflate until the object of interest is found. However, the usefulness of the algorithm on real medical images was not reported. Also based on active contour but in its level set representation, Yan [5] reported using fast marching method on

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lymph nodes in CT, in which they proposed a speed term which is based on both local image gradient and target region intensity features in dealing with the 'boundary leaking' problem. Due to disturbance of image noise, the detected lymph nodes may not be smooth enough and this is a limitation of using level set on structures with smooth boundaries. A stable 3D mass spring model (MSM) [6], which took the characteristic gray value range, directed contour information as well as shape knowledge into consideration, was employed by Dornheim et al. [7] for neck lymph node segmentation in 2007. However, a large number of parameters had to be adjusted carefully to ensure good performance and the varying size of the targeted structures would have a significant impact on the performance of the method. This drawback is partially addressed by Dornheim et al. [8] in another study using a multi-model strategy where each single model is specifically designed for a certain type of lymph nodes. Results improved from the original MSM. However, nodes with weak gradients at the border or deformed shape lead to worse results because of partly obscured border or shape information. The MSM model is further improved by Steger and Erdt [9] in 2010 using a size invariant mass spring model, which is less sensitive to the target structure's size than its predecessors and achieved an average dice similarity coefficient (DSC) of 0.72 over 25 lymph nodes in head and neck region from 11 CT datasets. Besides size invariant MSM, Steger et al. [10] proposed another method in 2011 to segment lymph nodes in the same body region. The closed contour is found by minimizing an energy function, which depends on gradients, intensities and shape priors, using dynamic programming. The average DSC improved to 0.81 using the new method. The algorithm is adapted to radiologists' behavior by including transition areas in intensity cost function. The DSC is further improved to 0.84. However, the method is highly heuristic and needs more investigation to claim for a general purpose.

Considering the above-mentioned challenges, snake model is the most suitable deformable method to accommodate lymph nodes variations in size and shape as well as to combine model-based formulations. In the literature, both Honea [4] and Yan [5] have reported using edge-based active contour for lymph node segmentation. But only results based on phantom images were examined and no quantitative measures were provided. In this paper, we investigated the performance of both edge-based and region-based snake in segmenting lymph nodes of the thoracic region on real CT images. We further developed a strategy to integrate both edge and region information in a constructive manner to improve its performance on lymph nodes segmentation. Section 2.2 explains in detail the implementation of *B*-spline snake models and the working of the new scheme. Section 3 reports our results. Sections 4 and 5 discuss the findings and draw conclusions.

2. Methods and materials

2.1. Dataset

Retrospective thoracic CT images from 8 lung cancer patients were included in the study, among which 18 pairs of suspicious lymph nodes growing over time were examined at both baseline and follow-up scans. In total, 36 lymph nodes were studied. The image was captured using Siemens Sensation Cardiac 64. Thorax routine protocol with source voltage 120 kV, current 125 mAs, rotation time 0.5 s, slice collimation 16×1.5 mm and slice width 5.0 mm, was used in the scan. The cross-sectional images were of size 512×512 pixel, with a voxel resolution $0.64\,\text{mm} \times 0.64\,\text{mm} \times 5\,\text{mm}$. These are standard CT images acquired for monitoring lung cancer treatment response. The lymph nodes in the study ranged from 1 to 3 cm in size and are of aortic, mediastinal, interlobar and hilar in their respective anatomic locations.

2.2. Snake models

In order to accommodate large variations in lymph nodes' morphology, snake models are considered to a suitable method for segmenting the structure. Given an image $I : \Omega \subset \mathscr{R}^d \to \mathscr{R}$, a snake model sets out to find a contour $x : \mathfrak{R} \to \mathfrak{R}^d$, such that it minimizes the energy function $\min_x E(x) = E_{external}(I, x) + E_{\text{internal}}(x)$. The external energy provides the driving for the contour to evolve while internal energy regularizes the smoothness of the contour obtained.

2.2.1. B-spline parameterization

Because of the smooth boundaries of lymph nodes, we choose the cubic *B*-spline for contour parameterization, which offers high flexibility, local control and computational efficiency [11]. A *B*-spline curve is a piecewise polynomial function defined as

$$x(s) = \sum_{i=1}^{N} B_{i,k}(s) P_i \text{ for } s \in [s_k, s_N] \tag{1}$$

where P_i represents the control points governing the contour, and $B_{i,k}$ represents their corresponding basis functions of degree k polynomial ($k = 3$ for cubic *B*-spline with the corresponding basis functions shown in Eq. (2)).

$$\begin{aligned} B_{0,3}(s) &= \frac{(1-s)^3}{6} \\ B_{1,3}(s) &= \frac{(3s^3 - s^2 + 4)}{6} \\ B_{2,3}(s) &= \frac{(-3s^3 + 3s^2 + 3s + 1)}{6} \\ B_{3,3}(s) &= \frac{s^3}{6} \end{aligned} \tag{2}$$

An important parameter of *B*-spline contour is the number of *B*-spline control points, which corresponds to the same number of *B*-spline segments for closed contours. Degrees of freedom, which measure the flexibility of the underlying contour and can translate into the ability of delineating structures in finer details, increase with increased number of control points. To study the effect of the number of control points on lymph nodes segmentation and determine an optimal number, the use of various numbers of *B*-spline control points (ranging from 6 to 24) were examined for both edge-based and region-based snake.

2.2.2. Edge-based snake model

For edge-based snake model, $E_{edge}(x, y) = -\int_0^1 g(x, y) ds$, where $g(x, y)$ is the edge- or gradient-driven energy landscape for snake to evolve. We made use of Canny edge detector, which was found effective in detecting lymph node boundaries [12], to derive partial lymph nodes edges. Distance transform of the edge map was calculated subsequently and used as the external energy to guide snake evolution.

2.2.3. Region-based snake model

Region-based snake was first proposed by Chan and Vese [13]. It assumes that the image has only two phases present, namely object and background. It attempts to separate the image into two different regions with maximum intensity separation.

$$E_{region}(x, y) = \lambda_1 \int_{\boldsymbol{R}_1} (I - \mu_1)^2 d\boldsymbol{x} + \lambda_2 \int_{\boldsymbol{R}_2} (I - \mu_2)^2 d\boldsymbol{x} + \lambda_3 \int_{\gamma} ds + \lambda_4 \int_{\boldsymbol{R}_1} d\boldsymbol{x}, \tag{3}$$

where is μ_1 the mean intensity of region R_1 enclosed by the contour and μ_2 the mean intensity of the outside region R_2. In our study, the parameters were fixed as $\lambda_1 = 0.6$ and $\lambda_2 = 0.3$ while λ_3 and λ_4 were taken to be zero as regularization on smoothness is implicit in general spline representation.