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Pulmonary Nodule Segmentation by using 3D Deformable Model in CT Images

Ji-Seok Yoon, Tae-Sun Choi

Gwangju Institute of Science and Technology,
123,Cheomdangwagi-ro,Buk-gu, Gwangju 500-712 Republic of Korea
{yjs,tschoi}@gist.ac.kr

Abstract. In this paper, we propose a pulmonary nodule segmentation method by using a 3D deformable model. First of all, the initial model is generated. The shape of the initial model is sphere which consists of triangle mashes. The model has internal energy and external energy. These energies are optimized to segment the nodule. Accordingly, the model is deformed through point normal vectors. After this process, the deformed models are evaluated. These processes are iterated until the model is converged.

Keywords: Segmentation, pulmonary nodule, CT image, 3D deformable model

1 Introduction

Lung cancer patients have low five-year relative survival rates, but the survival rates can be increased once the cancer is diagnosed early. However, the CT image consists of hundreds images regarding to patients, so it is difficult to be diagnosed via naked eye. Therefore, Computer Aided Diagnosis (CAD) system has to be studied. In the system, nodule segmentation process is necessary. Many proposed segmentation methods were that threshold and model based segmentation [1-2]. Jamshid Dehmeshki et al. proposed region growing based method [1]. In this reported method, the anatomical informations was essential. Therefore, it was critical weak point. In order to overcome the weakness, stable-mass spring model (SMSM) based segmentation method was proposed by D. Casico et al. [2]. The model consisted of sphere that was made of ring mesh in shape, and the model used two energies. The model did not be optimized the model energies. In order to overcome all of the problems and improve accuracy, we propose this method.

2 3D deformable model

In order to segment the pulmonary nodule from the CT image via model, the initial model is generated and optimized in image. The model consists of mesh which has shape of sphere. The model has two main energy: internal energy and external. In the model, internal energy is related with model shape which consists of basic structures

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(Fig. 1). Additionally, external energy is denoted by kinetic energy and potential energy. The model is deformed by using point normal vector until the model is converged.

2.1 Initial model generation

Generation of initial model is essential, once the nodule is segmented via proposed method. The model is spherical mesh which has triangle mesh structure to increase the accuracy of model optimization process (Fig. 1). Each mesh is connected with springs systematically. The sizes of all triangles has same size to make the stable condition.

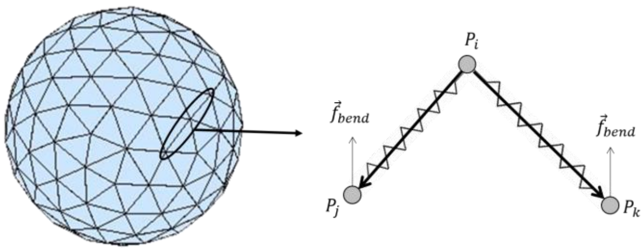

Fig. 1. Initial model of 3D deformable model and basic structure.

2.2 Model energy

The initial model has internal energy and external energy. Internal energy is shape energy, and defined by using the location and distance. It uses elastic energy, bending energy, and attraction energy as shape energy. The elastic energy is spring energy of the nearest points. The bending energy is sum of vectors that is made from one point and nearest points of the point. Additionally, attraction energy is normalized distance from the center of mass of point.

$$E_{int}(i) = \sum_{j=1}^{N_c} \frac{1}{2} k \left\| P_i - P_j \right\|^2 + \{ (P_j - P_i) + (P_k - P_i) \} + \frac{d_i}{\mu_d} \quad (1)$$

In this equation, k is spring constant. N_c is number of connection points, d_i is distance of points from the model's center of mass, μ_d is average of d_i, P_j and P_k are the point connected with P_i.

The external energy uses potential energy and kinetic energy. In these energies, intensity is potential energy and alteration of the intensity is kinetic energy.

Additionally, the nearest conditions are also altered in the image. Therefore, this conditions need to be calculated via 26-connected neighborhood.

$$E_{ext}(i) = |I(P_i)| - \|\nabla I(P_i)\| + \frac{\sum_{m=1}^{N_e} |I(P_m)|}{N_e} + \frac{\sum_{m=1}^{N_e} \left|I(P_m) - I(P_i)\right|}{N_e} \quad (4)$$

In this equation, N_e is the number of nearest points based on P_i. P_m is one of P_i's nearest points.

2.3 Model optimization

3D deformable model must be optimized to segment the nodule in the CT image,. The model optimization process has two processes: the model is deformed inside direction and outside direction via point normal vector. And then, these results are evaluated to find the minimum energy in three cases (original, inside, and outside deformation). These processes are working iteratively until the model is converged in the image.

3 Experimental results

We have experimented proposed method via Lung Image Database Consortium (LIDC) datasets [3]. From the datasets, 129 nodule datasets in 51 CT data is used. This datasets have. Proposed method uses the various sizes and types. We have scored them via relative absolute volume difference (RAVD), volumetric overlap error (VOE), and average symmetric surface distance (ASSD) [4]. These results show two difference type (qualitative results (Fig. 2), and quantitative result (Table 1)). Table 1 shows that proposed method is considerably improved compare with other methods.

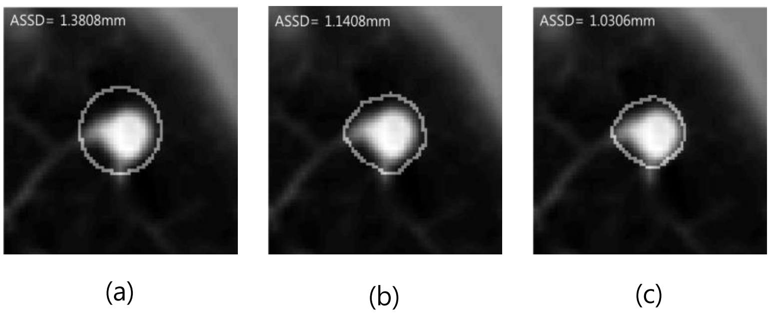

Fig. 2. Qualitative result of nodule segmentation (Juxtavascular nodule): (a) initial model, (b-c) optimization process

Table 1. Quantitative results of pulmonary nodule segmentation.

Method	RAVD(%)	VOE(%)	ASSD(mm)
Conventional	69.5016	72.4967	2.6746
SMSM	83.8247	85.6212	3.4977
Proposed	41.0489	49.1317	2.2076

4 Conclusion

In this paper, we proposed nodule segmentation method by using 3D deformable model. First, we generate the initial model. The model is spherical mesh which has triangle shapes in basic structures. The model has internal and external energy. Next, we optimize the initial model. In this process, the model is deformed and evaluated until the model is converged. Proposed method has been scored via RAVD, VOE, and ASSD. Proposed method is compared with conventional model and SMSM. Proposed method is considerably improved.

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