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3D robust Chan–Vese model for industrial computed tomography volume data segmentation

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ABSTRACT

Industrial computed tomography (CT) has been widely applied in many areas of non-destructive testing (NDT) and non-destructive evaluation (NDE). In practice, CT volume data to be dealt with may be corrupted by noise. This paper addresses the segmentation of noisy industrial CT volume data. Motivated by the research on the Chan–Vese (CV) model, we present a region-based active contour model that draws upon intensity information in local regions with a controllable scale. In the presence of noise, a local energy is firstly defined according to the intensity difference within a local neighborhood. Then a global energy is defined to integrate local energy with respect to all image points. In a level set formulation, this energy is represented by a variational level set function, where a surface evolution equation is derived for energy minimization. Comparative analysis with the CV model indicates the comparable performance of the 3D robust Chan–Vese (RCV) model. The quantitative evaluation also shows the segmentation accuracy of 3D RCV. In addition, the efficiency of our approach is validated under several types of noise, such as Poisson noise, Gaussian noise, salt-and-pepper noise and speckle noise.

1. Introduction

Since industrial computed tomography (CT) was invented, it has been widely applied in the fields for non-destructive testing (NDT) and non-destructive evaluation (NDE), such as aviation, railway, manufacturing, military industry [1,2]. At present, industrial CT systems typically use the projective data to reconstruct tomographic images. Being lack of spatial description of the workpiece, it is not very reliable to directly analyze 2D tomographic images. By contrast, analysis and processing based on 3D volume data will not only improve the reliability of image interpretation, but also can greatly promote the efficiency for technician. Many methods of image processing have been applied in the area of industrial CT, e.g., image enhancement, image segmentation, image registration and image measuring. Of these different techniques, image segmentation plays a fundamental role in numerous high level tasks such as object recognition, reverse engineering, as well as defect detection in CT images. Noteworthy is the fact that in practice, CT volume data to be dealt with may be corrupted by noise, which complicates many problems in image segmentation and makes it impossible for some widely used approaches to identify object regions. The principal sources of noise in digital images arise during image acquisition and transmission. For example, in acquiring images with CT scanning, light levels and sensor temperature are major factors affecting the amount of noise in the resulting image. Therefore, research on noisy image segmentation remains to be a challenging work in analysis of CT volume data.

Active contour models have drawn a lot of attention from many research areas and achieved the state-of-the-art performance recently, depending on its superiorities, such as sub-pixel accuracy and providing closed contours [3–8]. Most 2D segmentation methods for improving active contour models often focus on dealing with intensity inhomogeneity with the aid of localization idea [9–15]. Li et al. [11] proposed a Region-Scalable Fitting (RSF) model to overcome the difficulties caused by intensity inhomogeneities, by the use of the kernel function to illustrate intensity information in local region. Furthermore, based on the local intensity clustering property of the image intensities, Li et al. [15] proposed a novel region-based segmentation method which characterizes the local intensity information of image more

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appropriately. Due to the large-scale volume data, 3D improved methods [16–22] typically focus on dealing with the acceleration of algorithms. In the context of 3D segmentation, Mille [21] presented a narrow band region approach for deformable curves and surfaces in the perspective of 2D and 3D image segmentation, and Zhang et al. [22] proposed a fast multi-grid algorithm for solving the Chan–Vese model in three dimensions. Among aforementioned models, the well-known Chan–Vese (CV) model [8,23,24] has been successfully applied in image segmentation and computer vision. CV model is based on the assumption that the image is formed by two regions of approximatively piecewise-constant intensities, and it can segment object whose boundary is not necessary by gradient. However, since CV model only employs global intensity information of the image to detect boundary, it fails to segment images with intensity inhomogeneities or noise corruption.

In this paper, we present a 3D region-based active contour model—Robust Chan–Vese (RCV) model for noisy image segmentation in industrial CT volume data. Based on the same assumption with the CV model that image intensities are statistically homogeneous in each region, for each point in a region, a local energy is defined according to the difference between the intensities of all points within the neighborhood of the given point and the intensity average of the region. Then, for the whole image domain, a global energy is defined to integrate the local energy with respect to the neighborhood center. Finally, the overall energy term can be represented by a level set formulation, and the energy minimization process can be achieved when the surface is on the interface of the regions. Due to incorporating local neighborhood information for each point, even if some voxels are badly corrupted by noise, our model can still guarantee the deformable surface moves toward the desired object.

The rest of this paper is organized as follows. In Section 2 we first review the 3D CV model, and present the shortcomings of the 3D CV model, which motivates the work of this paper. Then we show how to effectively incorporate the localization idea into the 3D CV model to deal with noisy volume data in Section 3. In Section 4 we verify our method with experiments on industrial CT volume data. Finally, we end this paper by a brief concluding section.

2. The 3D CV model

Chan and Vese proposed a particular active contour model for 3D images [24], which is analogous to 2D version [8]. This model is formulated using the level set method [25,26] and based on a two-phase piecewise-constant segmentation. Consider a given gray level image $I:\Omega\rightarrow\mathbb{R}$, where $\Omega\subset\mathbb{R}^3$ is the image domain. Let Ω_1,Ω_2 be the distinct regions in Ω separated by the 2D surface C, such that $\Omega=\Omega_1\cup C\cup\Omega_2$ and $\Omega_1\cap\Omega_2=\varnothing$. Recall that in 3D images, the energy functional of the CV model is as follows [24]:

$$F_{CV}^{3D}(C,c_1,c_2)=\mu\cdot Area(C)+\lambda_1\int_{\Omega_1}|I(\mathbf{x})-c_1|^2\,\mathrm{d}\mathbf{x}+\lambda_2\int_{\Omega_2}|I(\mathbf{x})-c_2|^2\,\mathrm{d}\mathbf{x} \tag{1}$$

where $\lambda_1,\lambda_2>0$ are fixed parameters and point $\mathbf{x}(x,y,z)\in\Omega_i, i=1,2$. The first term in (1), with a weight μ, is introduced to regularize the surface C, while the last two terms are the data fitting terms. In a variational level set formulation, C is represented by the zero level set of a Lipschitz function $\phi:\Omega\rightarrow\mathbb{R}$, and the 3D CV model is formulated in terms of level set function as follows:

$$F_{CV}^{3D}(\phi,c_1,c_2)=\mu\int_\Omega|\nabla H(\phi(\mathbf{x}))|\,\mathrm{d}\mathbf{x}+\lambda_1\int_\Omega|I-c_1|^2H(\phi(\mathbf{x}))\,\mathrm{d}\mathbf{x}+\lambda_2\int_\Omega|I-c_2|^2(1-H(\phi(\mathbf{x})))\,\mathrm{d}\mathbf{x} \tag{2}$$

where H is the Heaviside function. Image segmentation is therefore achieved by alternately iterating the level set function ϕ and the constants $c_i, i=1,2$, that minimize the energy $F_{CV}^{3D}(\phi,c_1,c_2)$.

As is known that 3D CV model is a piecewise constant (*PC*) model, as it assumes that the image can be approximated by constants c_1 and c_2 in the regions Ω_1 and Ω_2, respectively. This model has achieved good performance in image segmentation task due to its ability of obtaining a widely evolvement range and handling topological changes flexibly [24]. Moreover, since this approach is a region-based model, it is capable of segmenting objects whose boundaries are not necessarily defined by gradient [8,27]. If, however, an image has been corrupted by certain noise, this model may lead to poor segmentation results owing to its global segmentation property of energy function defined.

3. 3D RCV model

As a general region-based model for image segmentation, 3D CV model does not consider local intensity information. If, however, an image has been corrupted by certain noise, CV model may obtain erroneous results, because noise may interfere with the surface evolution.

Recently, exploring the local information in image segmentation is getting more and more attention [10–13,15,28]. These approaches are typically used to deal with intensity inhomogeneity which always arises in medical imaging. In this paper, we try to address 3D industrial CT volume data segmentation in the presence of noise, by incorporating local intensity information into 3D CV model. For each point, we consider the intensity information of all the points in its neighborhood, while 3D CV model only uses single point intensity when formulating energy function. To be specific, we consider a spherical neighborhood with a radius r centered at point $\mathbf{x}\in\Omega$, denote by $N(\mathbf{x})$. We assume that, for a noisy volumetric image, not all the points within the neighborhood $N(\mathbf{x})$ are corrupted by the noise. Consequently, even if the point $\mathbf{x}$ is corrupted by certain noise, we can still adopt local intensity information of other points in $N(\mathbf{x})$ to guide deformable surfaces toward the correct position.

3.1. Local to global energy formulation

Consider a given gray level image $I:\Omega\rightarrow\mathbb{R}$, where $\Omega\subset\mathbb{R}^3$ is the image domain. Let Ω_1,Ω_2 be the distinct regions in Ω separated by the surface C, such that $\Omega=\Omega_1\cup C\cup\Omega_2$ and $\Omega_1\cap\Omega_2=\varnothing$. For a given point $\mathbf{x}(x,y,z)\in\Omega_i, i=1,2$, we define a local energy as follows:

$$e_{\mathbf{x}}^i=\int K_\sigma(\mathbf{x}-\mathbf{y})|I(\mathbf{y})-c_i|^2\,\mathrm{d}\mathbf{y} \tag{3}$$

where c_i is the mean intensity in Ω_i. $I(\mathbf{y})$ is the intensity value of $\mathbf{y}(x,y,z)$ in neighborhood $N(\mathbf{x})$, of which size can be controlled by the kernel function K_σ. In this paper, the kernel function is chosen as a truncated Gaussian kernel:

$$K_\sigma(\mathbf{u})=\begin{cases}\frac{1}{a}e^{-|\mathbf{u}|^2/2\sigma^2} & \text{for } |\mathbf{u}|\le r\\ 0 & \text{otherwise}\end{cases}$$

where a is a normalization constant and σ is the standard deviation of the Gaussian function. The role of kernel function K_σ is that it can be served as a neighborhood scalable term, which efficiently controls the range of neighborhood.