A NOVEL SPINAL VERTEBRAE SEGMENTATION FRAMEWORK COMBINING GEOMETRIC FLOW AND SHAPE PRIOR WITH LEVEL SET METHOD

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ABSTRACT

Segmentation of spinal vertebrae is extremely important in the study of spinal related disease or disorders. However, limited work has been done on precise segmentation of spinal vertebrae. The complexity of vertebrae shapes, with gaps in the cortical bone, internal boundaries, as well as the noisy, incomplete or missing information from the images have undoubtedly increased the challenge for image analysis. In this paper, we introduce a novel level set segmentation framework that integrates shape prior and the Willmore flow to drive the level set evolution. While the shape energy draws the level set function towards a range of possible prior shapes, the edge-mounted Willmore energy captures the localized geometry information and smooths the surface during the level set evolution. Experimental results on segmentation of spinal vertebrae from CT images demonstrate the powerful combination of prior knowledge and geometrical flow.

Index Terms— Vertebrae segmentation, level set method, Willmore flow, kernel density estimation, computed tomography.

1. INTRODUCTION

Vertebral fractures on specific region of vertebrae, e.g., cervical, thoracic, lumbar or sacrum, may occur due to injury, the unique anatomical structure of vertebrae and their functional features [1]. For instance, most fatal cervical spine injuries occur in upper level of cervical, either at craniocervical junction, namely C1 or C2, due to traumatic accidents. Fig. 1 shows a few examples of spinal disorders due to traumas and osteoporosis. In some cases, these fractures can cause damage to spinal cord and lead to neural deficits. Identifying severity of fractures and understanding its causes will help physicians determine the most effective pharmacological treatments and clinical management strategies for spinal disorders. An automatic technique which complements qualitative human judgement with precise quantitative measures is needed in medical practice. Detection and segmentation are the initial steps towards this quantitative framework. Although image segmentation has been a widely research area in computer vision and medical imaging, limited work has been done on detecting and segmenting vertebrae. The complexity of vertebrae shapes, gaps in the cortical bone, internal boundaries, as well as the noisy, incomplete or missing information from the medical images have undoubtedly increased the challenge in segmentation tasks.

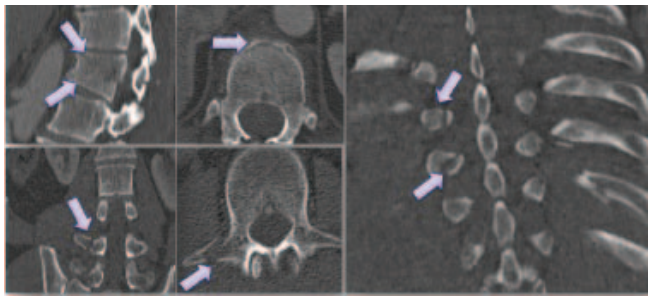


Fig. 1. Fractures of the vertebrae are indicated by arrows.

2. THE SEGMENTATION FRAMEWORK

2.1. Level Set Method

The level set method, also known as the implicit deformable model, embeds an interface in a higher dimensional function ϕ (the signed distance function) as a level set $\phi = 0$ [2]. The equation that governs the evolution of the level set function $\phi(t)$ is $\frac{\partial \phi}{\partial t} + F|\nabla \phi| = 0$, where F is the speed function. The level set method has been widely used for image segmentation. Recent developments of the methods however have largely focused on the variational framework. With this approach, an energy function $E(\phi)$ is defined in relation to the the speed function. The minimization of such energy generates the Euler-Lagrange equation, and the evolution of the

equation is through calculus of variation:

$$\frac{\partial \phi}{\partial t} = -\frac{\partial E(\phi)}{\partial \phi}.$$

In this paper, we consider the fusion of energies, i.e., using a shape prior distribution estimator E_s with an edge-mounted Willmore energy E_{w_0}:

$$E(\phi) = E_s + E_{w_0}.$$

In order to incorporate a given prior data set $\{\phi_1, \phi_2, \ldots, \phi_N\}$ into the level set segmentation framework, we adopt a shape dissimilarity measure based on the kernel density estimation discussed by Cremer et al [3]. This non-parametric distribution estimator overcomes two common shortcomings: (1) the assumption that the shapes are Gaussian distributed, which is generally inappropriate; (2) the shapes are represented by signed distance functions, which constitute a nonlinear space that does not include the mean.

2.2. Kernel Density Estimation

Kernel density estimation provides a fundamental smoothing estimator even with a small number of data samples. For N samples of shape models, the density estimation can be formulated as a sum of Gaussian of shape dissimilarity measures $d^2(H(\phi), H(\phi_i)), i = 1, 2, \ldots, N$:

$$P(\phi) \propto \frac{1}{N} \sum_{i=1}^{N} e^{-\frac{d^2(H(\phi), H(\phi_i))}{2\sigma^2}},$$

where $H(\phi)$ is the *Heaviside* function and

$$d^2(H(\phi), H(\phi_i)) = \int_\Omega \frac{1}{2} \left(H(\phi) - H(\phi_m)\right)^2 dx,$$
$$\sigma^2 = \frac{1}{N} \sum_{i=1}^{N} \min_{j \neq i} d^2(H(\phi_i), H(\phi_j)).$$

The segmentation is obtained by maximizing the conditional probability of ϕ given image intensity I:

$$P(\phi|I) = \frac{P(I|\phi)P(\phi)}{P(I)}$$

By considering the shape energy as

$$E_s(\phi) = -\log P(\phi|I),$$

the variational with respect to ϕ becomes

$$\begin{aligned}\frac{\partial E_s}{\partial \phi} =& \frac{\sum_{i=1}^{N} \alpha_i \frac{\partial}{\partial \phi} d^2(H\phi, H\phi_i)}{2\sigma^2 \sum_{i=1}^{N} \alpha_i} \\ =& \sum_{i=1}^{N} \frac{e^{-\frac{d^2(H\phi, H\phi_i)}{2\sigma^2}}}{2\sigma^2 \sum_{i=1}^{N} \alpha_i} \Bigg(2\delta(\phi) \Big[H(\phi) - H(\phi_i(x - \mu_\phi)) \Big] \\ &+ \int \Big[H(\phi(\xi) - H(\phi_i(\xi - \mu_\phi)) \Big] \\ &\delta\phi(\xi) \frac{(x - \mu_\phi)^T \nabla \phi(\xi)}{\int H\phi dx} d\xi \Bigg),\end{aligned}$$

where μ_ϕ is the centroid of ϕ and $\alpha_i = \exp\left(-\frac{1}{2\sigma^2} d^2(H\phi, H\phi_i)\right)$ is the weight factor for $i = 1, 2, \ldots, N$.

2.3. Willmore Flow

The Willmore flow is a function of mean curvature capturing the deviation of a surface from (local) sphericity. The associated energy function is formulated as

$$E_w = \frac{1}{2} \int_M h^2 dA,$$

where M is a d-dimensional surface embedded in $\mathbb{R}^{d+1}$ and h the mean curvature on M [4].

As a geometric functional, the Willmore energy is defined on the geometric representation of a collection of level sets. Its gradient flow can be well represented by defining a suitable metric, the Frobenius norm, on the space of the level sets. Frobenius norm is a convenient choice as it is equivalent to the l^2-norm of a matrix and more importantly it is computationally attainable. As Frobenius norm is an inner-product norm, the optimization in the variational method comes naturally. Based on the formulation by Droske and Rumpf [5], the Willmore flow or the variational form for the Willmore energy with respect to ϕ is

$$\frac{\partial E_w}{\partial \phi} = -\|\nabla \phi\| \left(\Delta_M h + h(t) \left(\|S(t)\|_2^2 - \frac{1}{2} h(t)^2 \right) \right),$$

where $\Delta_M h = \Delta h - h\frac{\partial h}{\partial n} - \frac{\partial^2 h}{\partial n^2}$ is the Laplacian Beltrami operator on h with $n = \frac{\nabla \phi}{\|\nabla \phi\|}$, $S = (I - n \otimes n)(\nabla \times \nabla)\phi$ is the shape operator on ϕ and $\|S\|_2$ is the Frobenius norm of S.

In order to ensure the smoothing effect by Willmore energy work nicely around the constructed surface and not affecting the desired edge of vertebrae, we propose to multiply the edge indicator function $g(I)$ with Willmore flow:

$$\frac{\partial E_{w_0}}{\partial \phi} = -g(I)\|\nabla \phi\| \left(\Delta_M h + h(t) \left(\|S(t)\|_2^2 - \frac{1}{2} h(t)^2 \right) \right),$$

where $g(I) = \frac{1}{1 + |\nabla G_\sigma * I|^2}$ and G_σ is the Gaussian filter with standard deviation σ.

3. EXPERIMENTAL RESULTS

The proposed segmentation framework was tested on 2D axial view of spinal vertebrae CT images of 15 patients. These images with pixel sizes of 512x512 are acquired from various CT scanners, Siemens, Philips, and Toshiba scanners. The level set method is implemented around a narrow band [6], with re-initialization [7]. The ground truths are manually segmented by medical experts. The leave-one-out approach is applied for cross validation and results are validated with the ground truth using the DICE score.

Fig. 2 compares the level set evolution using Caselles model [8], Willmore and edge-mounted Willmore energies. The Caselles energy fails to fully segment the spinal canal since partial edge information is missing. We observe from Fig. 2(c) & (d) that the Willmore energy maintains steady flow from initial contour with smooth level set evolution. However, this evolution is highly dependent on the initial contour, thus the segmentation must be accomplished with a proper guidance to achieve desired results. For example, with the edge-mounted Willmore energy, it moves towards the spinal canal. Fig. 3 shows segmentation results using the Chan-Vese model [9] with and without shape prior, with Willmore energy, as well as our proposed edge-mounted Willmore energy with shape priors. Obviously the Chan-Vese model is not able to capture the full vertebrae shape due to the low resolution nature of these images, even when the model is combined with prior shape energy. Note that the Willmore energy helps to capture finer details in the images but still, the segmentation results are poor. Only when the edge-mounted Willmore energy is combined with the prior shape energy, we manage to obtain the desired outcomes, i.e., the vertebrae shapes are nicely captured.

Samples of 3D segmentation of lumbar vertebrae using our proposed method are presented in Fig. 5. For validation with ground truth, the DICE score of the 2D segmentation results for Chan-Vese, Chan-Vese with shape prior and our proposed method are shown in Table1. In addition, the box plot diagram of DICE scores distribution for vertebrae segmentation results using our proposed method is demonstrated in Fig. 4. Clearly our proposed framework outperforms the other methods in terms of accuracy.

Energy	$L1$	$L2$	$L3$	$L4$	$L5$
E_{cv}	0.6887	0.6992	0.6825	0.6319	0.6739
$E_{cv} + E_s$	0.6953	0.7070	0.6865	0.6448	0.6835
$E_{cv} + E_w$	0.6939	0.6905	0.6914	0.6214	0.6863
$E_{w_0} + E_s$	0.9496	0.9425	0.9238	0.9264	0.9309

Table 1. DICE scores for segmentation results of lumbar vertebrae L1 to L5 using Chan-Vese, Chan-Vese with shape prior, Chan-Vese with Willmore and edge-mounted Willmore with shape prior approach.

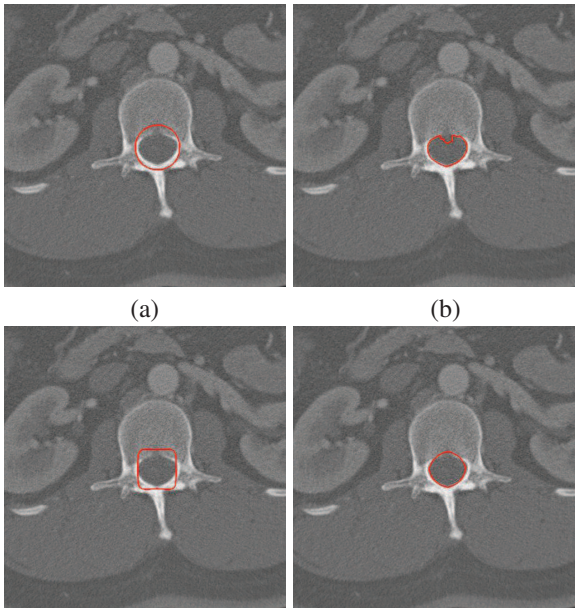


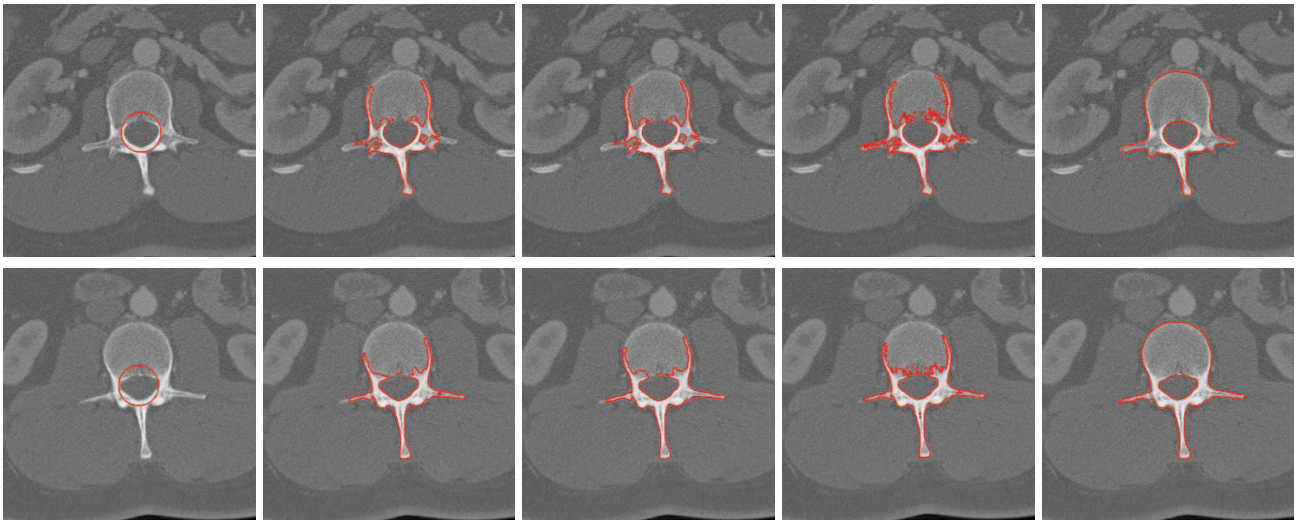
Fig. 2. (a) Initial contour. Segmented samples obtained by (b) Caselles, (c) Willmore, (d) edge-mounted Willmore approach.

4. CONCLUSIONS

We have presented a new level set segmentation framework for spinal vertebrae segmentation. The new framework combines the kernel density estimation technique and Willmore flow to incorporate prior shape knowledge and local geometrical features from images into the level set method. This complements our previous work on a new shape model for segmentation [10], and the identification of spinal vertebrae combining mathematical morphology and the level set method [11]. While the shape energy draws the level set toward prior shapes, the Willmore flow helps to regulate vertebrae shape in the process. The Willmore energy not only helps to retain the complex shape of vertebrae but also provides smoothing effect for the segmentation. To our knowledge, this is the first work on using Willmore flow for level set segmentation of spinal vertebrae. Experimental results on CT images of spinal vertebrae demonstrate the feasibility of our proposed segmentation framework. Future work is to further develop 3D segmentation of individual vertebraes and validate the results with ground truth. The ultimate goal is to provide an automated detection and segmentation framework for a quantitative platform for efficient and accurate diagnosis of spinal vertebrae fracture and other related diseases.

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(a) (b) (c) (d) (e)

Fig. 3. (a) Initial contours. Segmentation results obtained by (b) Chan-Vese, (c) Chan-Vese with shape prior, (d) Chan-Vese with Willmore, (e) edge mounted Willmore with shape prior approach.

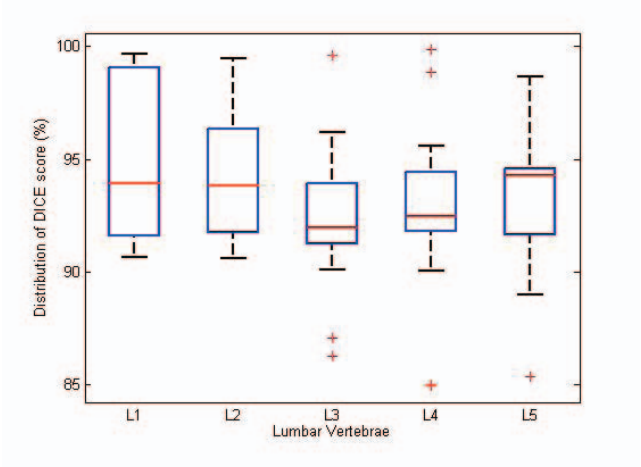


Fig. 4. Box plot diagram of DICE scores distribution for segmentation results of lumbar vertebrae L1 to L5 using edge-mounted Willmore with shape prior approach.

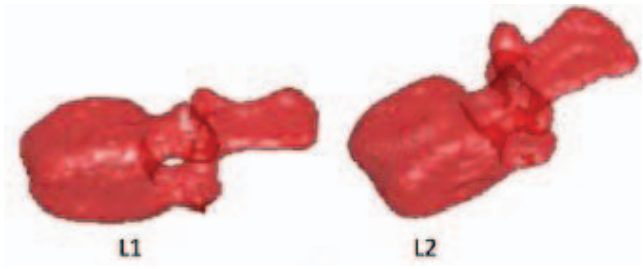


Fig. 5. 3D segmented samples of lumbar vertebrae L1 and L2 using our proposed method.

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