

# A Robust Segmentation Framework for Spine Trauma Diagnosis

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**Abstract** Accurate three-dimensional (3D) image segmentation techniques have become increasingly important for medical image analysis in general, and for spinal vertebrae image analysis in particular. The complexity of vertebrae shapes, gaps in the cortical bone and internal boundaries pose significant challenge for image analysis. In this paper, we describe a level set image segmentation framework that integrates prior shape knowledge and local geometrical features to segment both normal and fractured spinal vertebrae. The prior shape knowledge is computed via kernel density estimation whereas the local geometrical features is captured through an edge-mounted Willmore energy. While the shape prior energy draws the level set function towards possible shape boundaries, the Willmore energy helps to capture the detail shape and curvature information of the vertebrae. Experiment on CT images of normal and fractured spinal vertebrae demonstrate promising results in 3D segmentation.

## 1 Introduction

Accurate 3D spinal vertebrae image segmentation techniques are important tools to assist the diagnosis and treatment of spinal disorders such as spine trauma [10, 14]. Severe spine injury can result in life threatening and chronological problems unless treated promptly and properly. In any spinal injury, the possibility of spinal frac-

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ture must be examined immediately. Image segmentation of spinal vertebrae in 3D allows detection, measurement, and monitoring of the fracture(s), and facilitates biomechanics analysis of the spinal column.

Despite an increasing interest in spinal vertebrae segmentation in recent years, accurate 3D segmentation methods for diseased or fractured vertebrae are still lacking. There are some existing works in the literature for 2D or 3D segmentations, however they often require user intervention or fall short in achieving high accuracy [4, 6–8, 11–13, 15]. Segmentation of diseased or fractured vertebrae has been attempted recently [5, 19, 20], however, these are either in 2D or focused only on vertebral body rather than the whole 3D spinal vertebrae.

Traumatic injury of the spine often correlates with morphometric features in images. Segmentation of the whole vertebra in 3D would facilitate the detection of fractured vertebra and the assessment of the severity of the fracture. For example, the highlighted volumetric region of vertebrae could assist physicians in performing visual inspection of vertebral fractures, determining its stability and measuring quantitatively the fractured vertebrae.

This work extends the spinal vertebrae segmentation method presented in [9] to segment fractured vertebrae. In this case, high variability of fractured vertebral shape is largely captured by the embedded Willmore flow, while prior shape energy comes into action only when encountering inhomogeneous image intensity distribution.

## 2 Segmentation Framework

It is well-known that level set methods have advantages such as flexibility in dealing with topological change, easy extension into higher dimensions, as well as easy integration of prior knowledge and region statistic. The segmentation framework presented here has made use of these properties. The 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. Whilst the prior shape model provides much needed prior knowledge when information is missing from the image, the edge-mounted Willmore flow helps to capture the local geometry and smoothes the evolving level set surface.

The level set method embeds an interface in a higher dimensional function  $\phi$  (the signed distance function) as a level set  $\phi = 0$  [16]. The evolution of the level set function  $\phi(t)$  is governed by  $\frac{\partial \phi}{\partial t} + F|\nabla \phi| = 0$ , where  $F$  is the speed function. Based on the variational framework, 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 work, the fusion of energies whereby a shape prior distribution estimator  $E_s$  and an edge-mounted Willmore energy  $E_{w_0}$  is employed:

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

where  $\lambda$  ( $0 < \lambda \leq 1$ ) is the weight parameter, which is tuned to suit the segmentation of normal and abnormal spinal vertebrae.

## 2.1 Computing Prior Shape Energy via Kernel Density Estimation

Kernel density estimation (KDE) is a nonparametric approach for estimating the probability density function of a random variable. Without assuming the prior shapes are Gaussian distributed, KDE presents advantage in estimating the shape distribution even with a small number of training set, in addition to modeling shapes with high complexity and structure. In this study, we adopted the prior shape energy formulation discussed by Cremers et al. [2].

The density estimation is formulated as a sum of Gaussian of shape dissimilarity measures  $d^2(\phi, \phi_i)$ ,  $i = 1, 2, \dots, N$ :

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

where the shape dissimilarity measure  $d^2(\phi, \phi_i)$  is defined as

$$d^2(\phi, \phi_i) = \int_{\Omega} \frac{1}{2} (H(\phi) - H(\phi_m))^2 dx,$$

$$\sigma^2 = \frac{1}{N} \sum_{i=1}^N \min_{j \neq i} d^2(\phi_i, \phi_j),$$

and  $H(\phi)$  is the *Heaviside* function. By maximizing the conditional probability

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

and considering the shape energy as

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

the variational with respect to  $\phi$  becomes

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

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

## 2.2 Computing Local Geometry Energy via Willmore Flow

Willmore energy is a function of mean curvature, which is a quantitative measure of how much a given surface deviates from a sphere. It 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  $M$  [18]. For image segmentation, the Willmore energy provides an internal energy that gives a useful description of a region, where the effect of edge indicator is not significant. In these regions, smoothness of the shape of the curve should be maintained and extended, which can be regarded as a weak form of inpainting [3].

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 [3], the Willmore flow or the variational form for the Willmore energy with respect to  $\phi$  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  $\phi$  and  $\|S\|_2$  is the Frobenius norm of  $S$ .

**Table 1** Average DSC (%) and HD (mm) with standard deviation for segmentations of normal lumbar vertebrae (L1 to L5) using Chan-Vese (CV), Chan-Vese with prior shape (CV+S), Caselles (Ca), Caselles with prior shape (Ca+S), edge-mounted Willmore ( $W_0$ ), edge-mounted Willmore with prior shape ( $W_0+S$ ) energies, region growing (RG) and graph cut (GC) approach

Method	DSC (%)	HD (mm)
CV	37.68 ± 7.07	26.68 ± 2.18
CVS	45.09 ± 7.54	25.31 ± 2.38
Ca	55.75 ± 8.14	22.22 ± 1.57
CaS	71.12 ± 2.72	18.39 ± 1.15
W	75.82 ± 2.81	19.21 ± 1.51
<b>WS</b>	<b>89.32±1.70</b>	<b>14.30 ± 1.40</b>
RG	42.30 ± 11.43	25.20 ± 2.30
GC	13.23 ± 11.11	63.22 ± 14.82

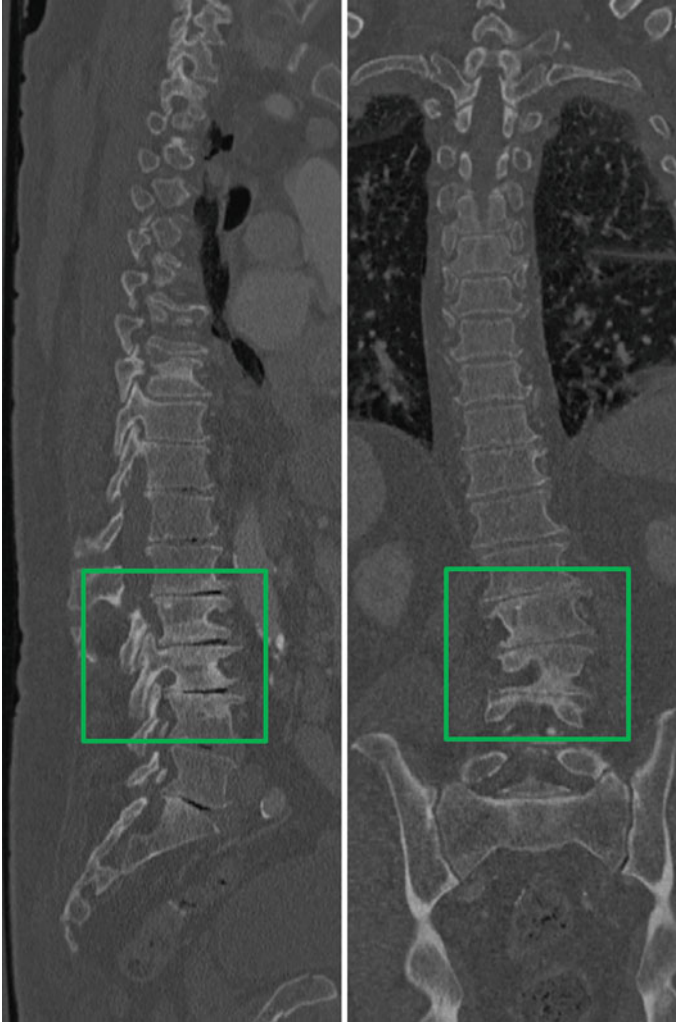
In order to ensure the smoothing effect work successfully around the constructed surface and not affecting the desired edge of vertebrae, the Willmore flow is coupled with the edge indicator function  $g(I) = \frac{1}{1+|\nabla G_\sigma * I|^2}$ , where  $G_\sigma$  is the Gaussian filter with standard deviation  $\sigma$ :

$$\frac{\partial E_{w_0}}{\partial \phi} = g(I) \frac{\partial E_w}{\partial \phi}.$$

### 3 Experiments and Results

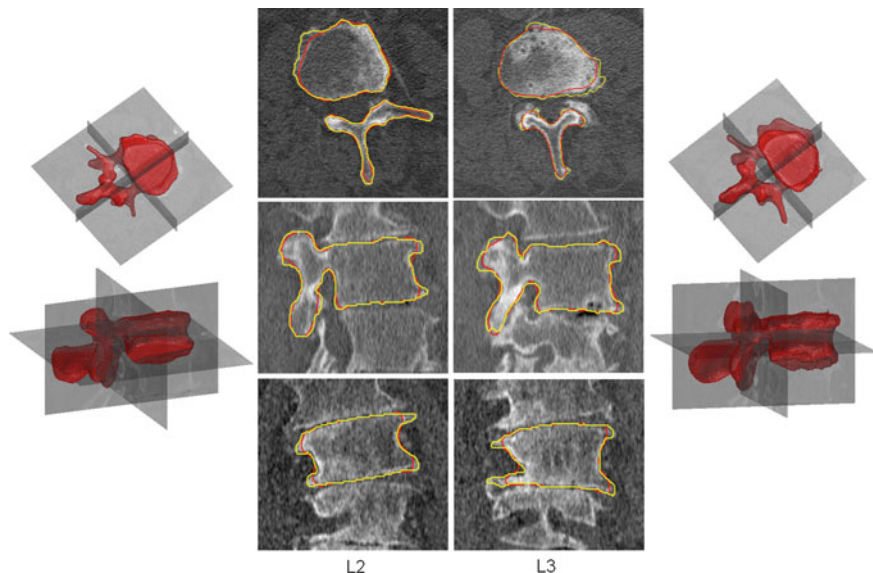
Experiments have been conducted on CT images of spinal vertebrae for 2D and 3D segmentation. The dataset consists of 20 CT images of normal and 4 CT images of fractured spinal vertebrae images of patients aged 18 to 66 years. The images were acquired from various CT scanners such as a 32-detector row Siemens definition, 64-detector row Philips Brilliance and 320-detector row Toshiba Aquilion. The in plane resolutions for these sagittal images range from 0.88 to 1.14 mm, with consistent slice thickness of 2 mm. Original images for these images have fixed sizes of  $512 \times 512$ , with number of slices varying from 45 to 98. For 3D segmentation, a torus is set manually surrounding the spinal canal as the initial contour. The level set method is then implemented using a narrow band scheme [1] with a re-initialization algorithm [17].

It has been reported that the 3D segmentations of spinal vertebrae clearly outperform the other methods such as region growing, graph cut, the classical level set methods such as Chan-Vese and Caselles models as well as their combinations with shape priors [9]. While some methods can perform relatively well in the 2D segmentation of spinal vertebrae, the majority of them fail badly when extended to the 3D segmentation of an individual vertebra due to the highly complex shape and connected structure as well as the nonuniform image intensity distribution in the pos-



**Fig. 1** An example of patient CT image with fractures on lumbar vertebrae L2 and L3

terior column of vertebra. Table 1 summarized 3D segmentation results on normal lumbar vertebrae using various approach, evaluated with ground truth. It is worth noted the effectiveness of our segmentation framework, with an overall accuracy of  $89.32 \pm 1.70\%$  and  $14.03 \pm 1.40$  mm based on Dice similarity coefficient and Hausdorff distance respectively, whilst the inter- and intra-observer variation agreements were  $92.11 \pm 1.97\%$ ,  $94.94 \pm 1.69\%$ ,  $3.32 \pm 0.46$  mm and  $3.80 \pm 0.56$  mm. Segmentation results depend highly on available dataset. The intra- and inter-observer variation estimations were performed to verify the difficulty of manual delineation in 3D using our dataset. We have shown that our results present no significant sta-



**Fig. 2** Different views of 3D segmentation for fractured lumbar vertebrae L2 and L3 as well as their projections in 2D (red) compared with manual segmentation (yellow) on axial, sagittal and coronal views

tistical differences ( $p > 0.05$ ) when compared with these observer estimations. The robustness of the proposed segmentation framework is demonstrated on the CT image of a patient with fractures on lumbar vertebrae L2 and L3 as seen in Fig. 1. As shown in Fig. 2, the segmentation framework manages to capture the 3D shape of fractured vertebrae L2 and L3, despite the inhomogeneity, noise and missing edges appeared on these fractured vertebra images. It enables individual segmentation of vertebrae without leaking into the nearby connected vertebra. Segmentation results on fractured vertebrae were evaluated via visual inspection by radiologist.

## 4 Discussion and Conclusion

An accurate level set segmentation framework for segmenting spinal vertebrae in 2D and 3D is presented in this study. The robustness of the framework is demonstrated on CT images of fractured vertebrae. The 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. It is worth noted that fusion of these energies effectively translate the prior shape knowledge and local geometrical feature of spinal vertebrae into the level set segmentation framework. The Willmore flow driven level set segmentation demonstrates better regularization than the widely used mean curvature flow in level set segmentation. Unlike minimizing

surface area by mean curvature flow in regularization, Willmore flow minimizes the bending energy when performing surface smoothing, which is more suitable for object with complex shape and structure. The segmentation algorithm was performed directly in a 3D volumetric manner instead of sequentially to the slices of a 3D image. This allows the volumetric tissue connectivity be taken into consideration and hence, enables more meaningful representation of 3D anatomical shape and structure. Moreover, it forms a continuous, smooth 3D surface and without the post processing redundancy posed by the slice by slice segmentation approach. More samples of fractured vertebrae are needed to perform further evaluation on the segmentation framework. Future work will integrate the algorithm into a pathological vertebrae characterization framework to yield an efficient computer aided diagnosis platform for quantitative analysis of spinal vertebrae fracture and related problems.

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