Active Contour Model with Shape Constraints for Bone Fracture Detection

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Abstract

This paper presents a segmentation method that outlines fractured bones in an X-ray image of a patient's arm within casting materials, and displays the alignment between the fractured bones. This segmentation task is often difficult because the casting materials cause a low contrast and high noise ratio in the X-ray images. A geodesic active contour model with global constraints is applied to this task. A prior shape is collected and used as a global constraint of our model. A maximum-likelihood function is derived to provide feedback for each evolving process. Experimental results show that the method produces the outlines of the fractured bones on the low contrast X-ray images robustly and accurately.

1 Introduction

Image segmentation is the process of dividing an image into meaningful regions, allowing a computer to 'see'. Image segmentation plays a key role in computer vision applications such as robotics, pattern recognition, and medical image analysis and has long been an area of active research.

Although many successes have been seen, image segmentation remains as a most challenging and difficult task and a fundamental goal in computer vision research.

Segmentation is especially difficult when images have a low signal-to-noise ratio or contain very complicated scenes where the objects in the image overlap (occluding and occluded objects produce poor contrast), or the object is embedded in a very noisy environment.

Image segmentation techniques can be divided into region based, edge based and active contouring based. Many existing methods such as thresholding, edge detection, region growing, watershed, active contouring are available in the literature. Each of the techniques has its own advantages and its own application areas. For example, thresholding can be applied to detect objects in an image where the foreground and background are well contrasted. Edge detection techniques search for gradient information in an image that defines the object whereas region growing techniques looking for the homogeneous regions to define the objects in an image. Watershed algorithms use markers to detect the number of objects in an image and try to find the boundaries between objects even where the gradient information is weakly defined by the image. Image segmentation techniques are application dependent. Each application has its own specific requirement. It is difficult to derive a generic solution to all image segmentation tasks.

Image segmentation is an essential task in medical imaging for diagnosis, treatment planning, and monitoring the progress of disease or the results of treatment. Extracting clinically useful information about anatomic structures imaged through CT, MR, PET, and other modalities is typically challenging. Image segmentation is a tool for surgical planning, radiotherapy planning, intraoperative navigation and tracking the progress of disease. More recently, medical images have been used to guide minimally invasive procedures. Although modern imaging devices provide an exceptional view of the human anatomy, the use of computers to quantify and analyze the embedded structures in the image with accuracy and efficiency is limited.

In this research, we address a unique and robust segmentation method and apply the method to detect the fractured bone and calculate the alignment of the fractured bone from an X-ray image of a human arm.

Segmenting fractured bones and determining bone fracture alignment on X-ray images are important aspects in assessing the success of fracture treatment. A computer aided diagnostic tool for detecting bone fractures and determining their alignment could save clinicians time by

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simplifying time-consuming and tedious tasks. The key part of designing this tool is to design a method to effectively segment the broken bones from the x-ray image; this would enable the alignment calculation. The overlaying cast produces additional noise, especially in the areas around metaphysis where the intensities appear as extremely blurry with very low contrast. Metaphysis and its background can barely be separated by traditional segmentation techniques. The inconsistent intensity pattern that changes from one X-ray to the next also causes difficulties in the segmentation process.

We apply our segmentation method to detect the fractured bone and able to calculate the alignment of the fractured bone from an X-ray images of a human arm. The human arm in the X-ray image is covered by casting material that interferes with the segmentation due to the low signal to noise ratio in the X-ray image created by overlapping casting materials. We combined techniques of segmentation and registration together in the segmentation process and we achieved good results.

We combined techniques of segmentation and registration together in the segmentation process and achieved good results. Traditionally, image analysis methods have viewed segmentation and classification or registration as separated processes. In fact, the two processes are closely related. Each can be improved with information that the other provides, as suggested by Schwartzkopt [1]: classification or registration would benefit from correct segmentation and segmentation often needs data from classification or registration. Our active contour model employs a prior shape as a global constraint allowing the model to evolve towards the desired shape and to register with the prior shape. We also apply mathematical morphology operations to abstract gradient information and geodesic distance transform to generate the narrow band for every evolving process. The advantages of using mathematical morphology operations to detect image gradient is that the shape and size of the noise feature of casting material can be reduced by specifying the structuring elements that are larger than the noise shape. Therefore, we use dilation and erosion with a structuring element that represents the characteristics of the casting material to generate a gradient image. We also use signed distance transform to generate a narrow band for the curve evolving process. Moreover, we provide estimates of confidence in the matching process to provide feedback to the evolving process. The contributions of this research are as follows:

Embeds global constraints in the evolving process to guide the growth of the curve;Employs mathematical morphology operations to perform noise reduction, edge detection and narrow band generation;Uses signed distance transform to create a narrow band for the curve evolving process; Provides estimates in the matching process that ensure the matching process converges; and detects the bone fracture and alignment accurately.

2 Background

Image segmentation techniques can be classified into several different approaches such as edge detection, region growing, morphological operations, watershed, and active contour models. Edge detection and region growing techniques are suitable to the segmentation tasks where the gradient information of object boundaries is clearly defined. Weak gradients around the object boundaries could cause segmentation failures. Watershed algorithms provide a tool to segment objects in the images that overlap. Separating the overlapping objects using a watershed algorithm is faster and more robust than using edge detection or region growing techniques.

Deformable models provide a robust foundation for the representation, simulation, and manipulation of the complex non-rigid anatomical structures [2]. The potency of deformable models stems from the segmentation of anatomic structures by exploiting constraints derived from the image data together with a priori knowledge about the location, size, and shape of these structures. Deformable models have been used to segment, visualize, track and quantify a variety of anatomy structures including the brain, heart, face, kidney, lung, stomach, liver, skull, vertebra, brain tumors, a fetus and even cellular structures such as neurons and chromosomes [2][3][4].

2.1 Snakes versus Level sets

In recent years, deformable model-based image segmentation has seen the emergence of two competing approaches: snakes and level-sets.

Snakes can be viewed as *Lagrangian* geometric formulations wherein the boundary of the model is represented in a parametric form. The deformation energy function is minimized with 'internal' and 'external' energies along its boundary. The geometric information is considered to be internal energy and image gradients are external energy. The models act like elastic bodies that stabilize when the deformation energy function is minimized.

The level-set method [5, 6] for image segmentation has been extensively evaluated over the last few years. The level-set method provides a mathematical formulation for tracking the motion of a curve including optimal path planning which can be recast as front propagation problems. The evolving constraints for propagation of an interface can be defined in the problem domain by exploiting constraints derived from the image data.

A geodesic active contour model has the advantages of both the snake and level-set methods and presents some positive properties. The model mathematically inherits the way it handles the topological changes from the level-set method and the minimizing deformation energy function with 'internal' and 'external' energies along the boundary from the traditional snake method by transforming a mathematical formulation of snake with partial differential equations (PDEs). It deforms a given curve with a PDE and obtains the desired result as the solution of the PDE.

A level-set model uses a function that depends on the image gradient as an edge detector to stop the curve evolution [5]. The model can only detect objects defined by the gradient. This type of segmentation using only local information has often been frustrating when used in poorly-contrasted regions due to occluding and occluded objects or high noise and is often enhanced by the use of prior shape information. Shape is a powerful property to distinguish an object from its surroundings in an image. Shape is commonly used to complete the information provided by local properties of the image. A computerized method should utilize shape information like a human would identify an object's appearance in an image by both its shape and by the view of the object. In medical imaging, geometric shape models provide extrinsic information about objects and are often incorporated explicitly, especially for the segmentations where prior shape information can be collected. Several methods of incorporating prior shape information into the boundary determination of level-set have been developed. Staib and Duncan [7] introduced a parametric point model based on an elliptic Fourier decomposition of the landmark points. The parameters of their curve are calculated to optimize the match between the segmenting curve and the gradient of the image. Wang and Staib [8] applied a statistical point model for the segmenting curve by using principal component analysis to the covariance matrices that capture the statistical variations of the landmark points. Leventon et al [9] incorporated shape information as a prior model to restrict the flow of the geodesic active contour. Their shape model is derived by performing principle component analysis on a collection of signed distance maps of the training shape. The curve evolves according to two competing forces: the gradient force and the force exerted by the estimated shape where the parameters of the shape are calculated based on the image gradient and the current position of the curve. Chen [10] proposed a model that uses the geodesic contour model and an "average shape" as the prior shape which defines a term in the evolving function of the model. This approach showed potential for image segmentation incorporating a shape that can be collected before hand. The active contour model proposed in this paper is motivated by the method described by Chen [10]. In our approach, the global constraints such as shape, rotation, scale, and translations are incorporated into the level-set evolving process. The curve propagates with a velocity depending on the image gradients and the prior shape information. The propagation stops when the active contour arrives at high gradients or closely matches the prior shape.

2.2 Mathematical morphology

Mathematical morphology theory [11] defines computing operations by primitive shapes. Mathematical morphology provides tools for measuring topological shape, size, and location. '**Set Theory**' is used as the foundation for many functions. The basic functions are '**Dilation**' and '**Erosion**'. Isolating certain features of the image can be accomplished by the *top-hat transform* [11]. Top-hat transform can be used to select the defined features by defining the larger structuring element of that shape.

2.3 Mutual Information

We also employed mutual information (MI) in our model to measure the difference between curves. Mutual information provides a function of transformation between images. MI is commonly used in medical imaging for image registration [12]. MI is a quantity that measures the mutual dependence of two objects. It measures the information about object X that is shared by object Y. In image registration applications, given a reference image (e.g. a brain scan), and a second image which needs to be put into the same coordinate system as the reference image. The second image is deformed until the mutual information between itself and the reference image is maximized. In our method, the evolving curve deforms until the mutual information between the curve and the prior shape is maximized. Different transformations are evaluated to find the maximum of MI.

3. Method

3.1 Active contour model - Level-Set Method

Consider that a curve moves in a direction normal to itself with a speed function F. Assuming $F > 0$, the front always moves "outward" [5]. The front always moves "inwards" when $F < 0$.

Evolution equation for Φ:

$$\phi_t + F \parallel \nabla_x \phi \parallel = 0 \quad \text{on} \quad \Omega \qquad \textbf{(1)}$$

$$\phi(0, \bullet) = 0 \quad \text{on} \quad \partial\Omega$$

Boundary value equation:

$$F \parallel \nabla_x T \parallel = 1 \text{ on } \Omega \quad T = 0 \quad \text{on} \quad \partial\Omega$$

3.2 Signed distance transform

The distance transform [12] is also used in our method to formulize narrow bands in our evolving process. Figure 1 give an example of distance transform on a rectangular shape.

0	0	0	0	0	0	0	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	0	0	0	0	0	0	0

→

0	0	0	0	0	0	0	0
0	1	1	1	1	1	1	0
0	1	2	2	2	2	1	0
0	1	2	3	3	2	1	0
0	1	2	2	2	2	1	0
0	1	1	1	1	1	1	0
0	0	0	0	0	0	0	0

Figure 1: A distance transform for a simple rectangular shape.

In our approach, the Φ is achieved by using a signed distance function for each numerical iteration. The distance from zero level set is computed towards outside of the zero level set. A contour tracing algorithm is used to achieve this distance function. One nice property of a distance map is its unit gradient magnitude is the same in all directions. A regenerating Φ function uses a distance map by recalculating the distance map after each evolving process. The narrow band for the curvature flow $|\nabla\Phi|$ is then increased by 1 in each iteration. The driving force is taken as $F > 0$, and the curve evolves outward. The gradient image is generated by using morphology gradient operations (erosion subtracted from dilation). The structuring element used is a 5x5 square which represents the shape and the size of the casting materials in the X-ray image. The narrow band for the curvature flow $|\nabla\Phi|$ is then increased to 3 which will cover half of the 5x5 square, the same size as the structuring element of the morphological gradient operation.

3.3 TopHat transform

$$\text{TopHat}(A, B) = A - (A \circ B) = A - \max_B(\min_B(A)) \qquad \textbf{(2)}$$

where the structuring element ***B*** is bigger than the objects to be detected and similar to the shape of the objects. Figure 2 gives an example of TopHat transform.

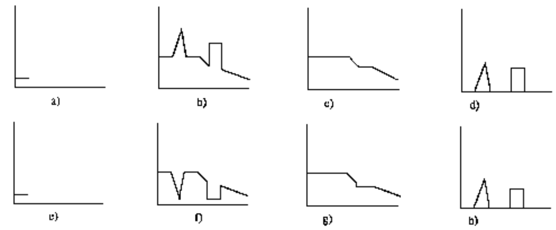

Figure 2: a,e) structuring element; b,f) original image; c,g) opening (resp. closing); d,h) result from subtraction

3.4 Mutual Information

The information that X tells about Y is the uncertainty in X plus the uncertainty in Y minus the uncertainty in both X and Y [13]. A series of statements regarding entropy are:

$$I(X;Y) = H(X) - H(X|Y);$$
$$I(X;Y) = H(Y) - H(Y|X);$$
$$I(X;Y) = H(X) + H(Y) - H(X,Y);$$
$$I(X;Y) = I(Y;X); \; I(X;X) = H(X);$$

3.5 Shape Model

The standard shape model used to define the shape information described in this paper is collected from the initial X-rays obtained prior to cast application. The segmentation on this X-ray image using the level-set method introduced by Jiang [14] produces accurate results. Following cast placement, segmentation can be quite problematic.

3.6 Curve Evolving with global constraints

Suppose two contours, C_1 and C_2, have the same shape. Then there exists a scale S, a rotation matrix R with respect to an angle θ, and a translation vector T such that C_1 coincides with:

$$C_2^{new} = SRC_2 + T \qquad \textbf{(3)}$$

Following the principle in (4), our active model is designed to employ a new term: a prior shape. Therefore the new active model is described as:

Let $C(p) = (x(p), y(p))$ ($p \in [0,1]$) denote a differentiable parameterized curve in an image I. Let C^* be a curve representing the shape prior, and $g|\nabla I(x,y)|$) be the function defined as:

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$$g|\nabla I(x,y)|) = 1/(1+|\nabla I(x,y)|^2) \quad \textbf{(4)}$$

To get a smooth curve C that captures higher gradients, the arc-length of C in the conformal metric $ds = g|\nabla I(x,y)|)C(p)|C(p)|dp$ is minimized. To capture the shape prior C*, the curve C and the transformation S, R, T is calculated such that the curve $C^{new} = SRC + T$ and C^* are perfectly aligned. The energy function to be minimized is:

$$\min_{C,\mu,R,T} \int_0^1 \{g(|\nabla I|(C(p))) + \frac{\lambda}{2} d^2(\mu RC(p)+T)\} |C'(p)| dp \quad \textbf{(5)}$$

Where $\lambda > 0$ is a parameter, and $d(x,y) = d(C^*, (x,y))$ is the distance of the point (x,y) from C* . The minimization problem now can be solved by finding steady state solutions to the following system:

$$\frac{\partial C}{\partial t} = -vn, \ C(0,p) = C_0(p) \quad \textbf{(6)}$$

$$\frac{\partial \mu}{\partial t} = -\lambda \int d\nabla d \cdot RC \ |C'(p)| dp, \ \mu(0) = \mu_0$$

$$\frac{\partial \theta}{\partial t} = -\lambda\mu \int d\nabla d \cdot (\frac{dR}{d\theta} C) |C'(p)| dp, \ \theta(0) = \theta_0$$

$$\frac{\partial T}{\partial t} - \lambda \int d\nabla d \cdot |C'(p)| dp, \ T(0) = T_0$$

The curve evolves as:

$$v = \nabla g \cdot n + gk + \lambda s(d\nabla d) \cdot (Rn) + \lambda d^2 k \quad \text{(7)}$$

where n is the outward unit normal to C, and k is the curvature of the curve C. The function d is evaluated at $SRC(p) + T$. The mutual transformation function is defined as: max(AreaOverlap(CruveA, CurveB) and min(CurveDifference(CurveA,CurveB).

4 Result

We have tested our algorithm on more than 10 cases. The results showed that our algorithm is robust and accurate. Figure 3 shows some of the result. The final evolving process is in yellow colour, and the blue colour shows the initial position of the evolving curve. The initial curve evolved till the energy of the evolving function is minimized.

One case failed to segment successfully by our algorithm in which the fracture can barely recognized by our expert radiologist due to poor contrast of the image. Some results are presented in Figure 3 and Figure 4.

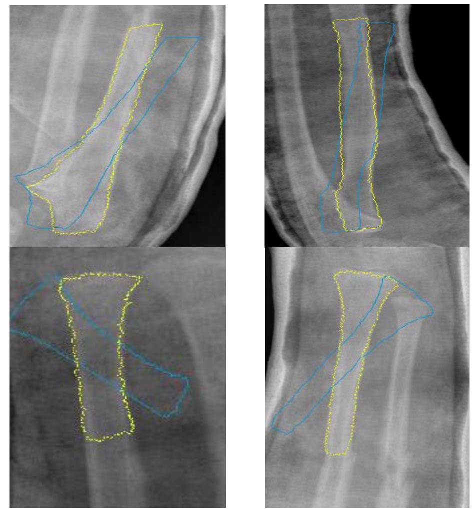

Fig. 3. Experiment results: Blue color shows the initial curve, yellow color shows the final result.

Fig. 4. Bone Alignment calculation result

5 Discussion

We have provided a model-based segmentation method that can be used to segment fractured bones on the X-ray image of a human arm. Our method can also be applied to other segmentation tasks. Our approach is computational efficient and produces accurate segmentation result. Future work to this research project is to investigate an automatic curve initialization procedure.

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References

[1]Schwartzkopt, W. C., Bovik, A. C., Evans, B. L.: Maximum-Likelihood Techniques for Joint Segmentation-Classification of Multispectral Chromosome Images. *IEEE transactions on medical imaging*. 24 (2005) 1593–1610

[2]McInerney, T., and Terzopoulos, D.: Deformable models in medical image analysis: A survey. *IEEE Computer Society*, (1998) 127-146

[3] Kass, M., Witkin, A., and Terzopoulos. D., Snakes: Active Contour model, *International Journal of Computer Vision*, (1988) 321-333

[4]McInerney, T., and Terzopoulos, D., Topologically adaptable snakes, in proceedings of the International Conference on Computer Vision, *IEEE Publications*, Los Alamitos, CA, (1995)

[5] Sethian, J. A.: Level Set methods and fast marching methods, Cambridge Press, 1999

[6] Sapiro G.: Geometric Partial differential equations and image analysis, Cambridge University Press, New York (2001)

[7] Staib, L., and Duncan, L.: Boundary finding with parametrically deformable models, *IEEE transactions on pattern analysis and machine intelligence*, 14 (1992) 1061-1075

[8]Wang, Y., and Staib, L.: Boundary finding with correspondence using statistical shape models, *Proceedings from IEEE Conference on Computer Vision and Pattern Recognition*, (1998) 338 – 345

[9]Lenventon, M. E., Grimson, W-E. L., and Faugeras, O.: Statistical shape influence in geodesic active contours, *Proceedings from IEEE Conference on Computer Vision and Pattern Recognition*, (2000) 316 – 323

[10]Chen, Y., Thiruvenkadam, S., Tagare, D. H., et al :On the incorporation of shape priors into geometric active contours, *Proceedings from IEEE Workshop on Variational and Level set method*, (2001) 145-152

[11]Serra, J.: Mathematical morphology, Academic Press, (1982)

[12] Rosenfeld, A. and Pfaltz, J.: Distance Functions on Digital Pictures, *Pattern Recognition*, Vol. 1, (1968) 33 – 61

[13]Peng, H., Long, F., Ding, C.: Feature selection based on mutual information: Criteria of Max-Dependency, Max-Relevance, and Min-Redundancy, *IEEE transactions on pattern analysis ands machine intelligence*, 27 (2005) 1226-1238

[14]. Y jiang, X-ray bone fracture subtraction using geodesic active contour and mathematical morphology operations, *Computer Assisted Radiology and Surgery*, London, UK, (2003)