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X-ray image segmentation using active contour model with global constraints

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Abstract. This paper presents an image segmentation method that outlines fractured bones in an X-ray image of a patient's arm within cast materials, and displays the alignment between the fractured bones. The cast material overlaying on the fractured bones creates extra noises to the X-ray image and provides challenges to the segmentation method. Our segmentation method aims on outlining the objects from a low contrast and high noise ratio of the X-ray images. A geodesic active contour model with global constraints is applied to this segmentation task. A prior shape is collected and embedded into the active contour model as a global constraint. A maximum-likelihood function is derived and used as a feedback system for each evolving process to a decision making procedure. Mutual Information is employed to measure the difference or the likelihood between the prior shape and the evolving curve. Experimental results show that the method produces the outlines of the fractured bones on the low contrast X-ray images robustly and accurately. The computation of our segmentation method is fast and efficient.

1 Introduction

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 simplifying the time-consuming and tedious task. 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 most difficult part of this segmentation task is to overcome the noisy background caused by the overlaying cast, especially in the areas around metaphysis where the bone objects 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. In this research, we address a unique and robust segmentation method that specialized on the segmentation from the very noisy images. We apply our method to detect the fractured bone.

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 as a fundamental goal in computer vision research. The common difficulties for segmentation tasks are the ones that the images to be processed have a low signal-to-noise ratio or contain very complicated scenery 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 is also 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. Recently, medical images have been used to guide minimally invasive procedures for patient's treatment. 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 due to the sheer size of the images and the technologies used for processing the images. An extensive amount of research needs to be done.

As there are many segmentation techniques available, a generic algorithm for solving all segmentation tasks has not been born yet. In this research, we combined the techniques of segmentation and registration into a single segmentation process. Traditionally, image analysis methods view the segmentation and 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]. Registration would benefit from correct segmentation and segmentation often needs data from registration or classification.

We applied active contouring model with shape information as the model constraints. A prior shape is collected and employed in our model that allowing the model to evolve towards the desired shape. We also applied mathematical morphology operations to abstract gradient information for controlling the speed and geodesic distance transform for generating the narrow band for each curve evolving process. The advantages of using mathematical morphology operations to detect image gradient is that the shape and size of the noise feature can be defined and then removed by specifying the structuring elements that are larger than the noise shape in the morphological filtering process. Thus, we use dilation and erosion operations with the structuring element size that represents the characteristics of the cast material to create a gradient image instead of using traditional edge detection algorithms. Moreover, our method provides the estimates of the confidence level in each evolving process and generates system feedback to the next iteration.

The main contributions of our research are summarized as follows:

1. Embeds global constraints in the evolving process to guide the growth of the curve;
2. Employs mathematical morphology operations to perform noise reduction, edge detection and narrow band generation;
3. Provides estimates in the matching process that ensure the matching process converges; and
4. Applied the model to bone fracture and alignment.

2 Background

Deformable models provide a robust foundation for the representation, segmentation, and manipulation of complex objects in an image. Recent developments on segmentation are favor with using deformable models due to some of the nice properties of the deformable models which result in efficient segmentation algorithms. Robust segmentation can be achieved by studying the mathematical constraints of the model. In medical imaging applications, 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

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.

Level-set method [5] [6] provides a mathematical formulation for tracking the motion of a curve which can be recast as front propagation problems. The deformation of the Level set method depends on the evolution process of the initial curve and can be defined by its mathematical formulation. The important key to achieve segmentation using level set method is to control the speed of the curve evolving. The evolving constraints for propagation of an interface can also be defined in the problem domain by exploiting constraints derived from the image data.

A geodesic active contour model that appeared in the literature after the snake and the level set method took the advantages of both the snake and level-set methods. 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).

There are still some drawbacks for the Level-set methods that use a function depending 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 being 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. 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. This research is specifically aimed on how to incorporate shape constraints to the level set method.

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 in an image. '**Set Theory'** is used as the foundation for many morphology operating functions. Isolating certain features of the image can be accomplished by the *top-hat transform* [11]. Top-hat transform can be used to select the object by defining a structuring element larger than the shape of the object.

2.3 Mutual Information

We also employed mutual information (MI) in our model to measure the difference between the evolving curve and the prior shape. Mutual information provides a function of transformation between images and is a quantity that measures the mutual dependence of two objects [13]. It measures the information about object X that is shared by object Y. The similarity between the prior shape and evolving curve is defined by MI in our active model and used as the feedback to the next curve evolving process.

3. Method

Before applying deformable models, we have reviewed some methods for segmenting bones from X-ray images. We were not able to find a satisfactory method for this task. Deformable models were being selected and studied for this segmentation task.

3.1 Active contour model - Level-Set Method

Consider a curve moves in a direction normal to itself with a speed function F. Assuming F > 0, the front always move "outward" [5]. Figure 1 gives a graphic description of the curve movement in 2D and 3D.

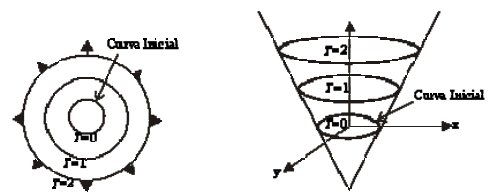

Fig.1: Transformation of front motion in 2D and 3D

Evolution equation for Φ: **(1)**

$$\phi_t + F \parallel \nabla_x \phi \parallel = 0 \quad \text{on } \Omega$$
$$\phi(0,\bullet) = 0 \quad \text{on } \partial\Omega$$

Boundary value equation:

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

3.2 Signed distance transform

The distance transform [9] is used in our method to formulize narrow bands in our evolving process. In our approach, the Φ is achieved by using a signed distance function for 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 Basic morphology operations and TopHat transform

'**Opening**' can be expressed as a composition of an erosion followed by a dilation, both by the same input structural element. '**Closing**' can be expressed as composition of a dilation followed by an erosion. Gray-scale openings and closings by appropriately selecting the structuring element size and shape have the property of removing image details. Opening removes the features that smaller than the structuring element, the rest of the signal is left unchanged.

3.3.1 Residue

The residue is a generic name for what is left something is removed. For instance if we clean or filter something, the residue is what did not pass on the filter. Having two operators, one larger that the other, the residue can be computed by their difference.

$$R = \Psi_1 - \Psi_2 \,,\, if\ \Psi_1 \geq \Psi_2$$

3.3.2 Gradient

Image gradient can be obtained from the dilations and erosions. Gradient is a composition of three basic operators: a dilation and an erosion of the input image by the input structuring element and a subtraction of these two results. In our approach, the gradient image is generated by subtracting the original image from the dilated image with a square structuring element of size 7.

3.3.3 Top-hat transform

Isolating some feature of the image can be accomplished by the top-hat transform [11]. It is a very powerful tool in mathematical morphology applications since many segmentation tasks require isolate some kinds of features in a given image. Top-hat transform can be used to select the defined features by defining the bigger structuring element of that shape.

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

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

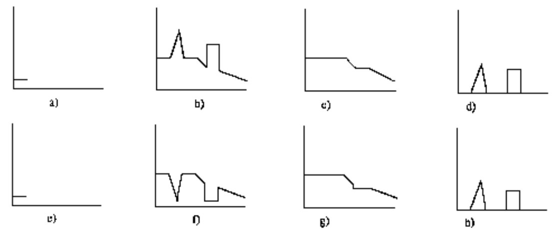

Figure 2: a,e) structuring element; b,f) original image; c,g) opening (resp. closing); d,h) result from subtraction

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:

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

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

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 color of the object. Incorporating shape information into our recognition process is explained in this section. 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:

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

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

$$g|\nabla I(x,y)|) = 1 / (1 + |\nabla I(x,y)|^2) \qquad (4)$$

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:

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

Where λ > 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:

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

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

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

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

The curve evolves as:

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

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 below:
max(AreaOverlap(CruveA,CurveB)
min(CurveDifference(CurveA,CurveB)

4 Result

We have tested our model on more than 20 cases of human arm data set. The initial curve is manually located within the piece of the bone to be segmented. Our algorithm allows the curve evolving towards the model and the model adjusts itself towards the curve. The model provides an evolving constraint to the evolving curve and limits the curve grow within the shape of the model. The algorithm performs this segmentation task efficiently. There is one failed case that the fractures in the X-ray image can barely recognized by our expert radiologist due to poor contrast of the image. Some results are presented in Fig.3 and Fig.4. Figure 3 presents some of the segmentation results. Figure 4 shows the alignment calculation after the segmentation process.

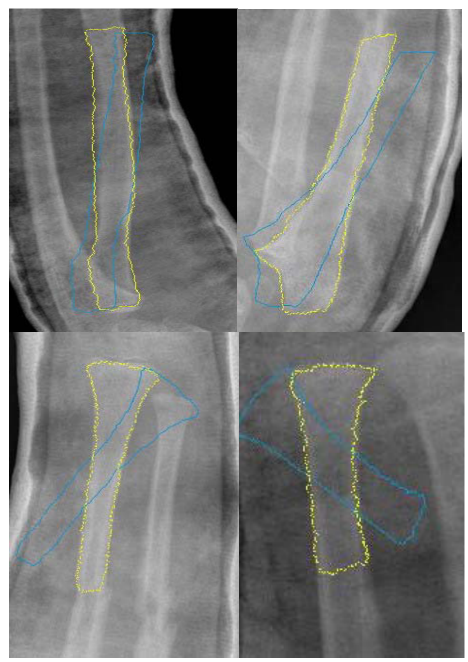

Fig. 3 Experiment results : Yellow colored curves are the initial curves and the blue colored curves are the final segmentation results.

Fig. 4 Alignment calculation based on the segmentation result.

5 Discussion

We have provided a model-based segmentation method that segments the fractured bones on the X-ray image. Our method can be applied to other segmentation tasks. This approach is computationally efficient and robust. Future work will be to investigate an automatic curve initialization procedure.

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