MEASUREMENTS OF BLOOD VESSEL WALL AREAS IN BLACK-BLOOD MR IMAGES USING GLOBAL MINIMUM SNAKE ALGORITHM *

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ABSTRACT

In this paper, we propose a novel boundary detection approach for three-dimensional shape modeling. Our method is based on finding surfaces of minimal weighted area in a Riemannian metric. In order to take advantage of intensity information of images, we further integrate this intensity information into the boundary detection algorithm. We apply this algorithm to identify the inner and outer boundaries of the blood vessel wall in magnetic resonance images, and assess its accuracy and reproducibility. Our algorithm is reasonably accurate (about 2% difference in comparison with the manual method) and highly reproducible.

1. INTRODUCTION

The original Snake model was introduced by Kass, Witkin, and Terzopoulos [8]. A Snake is an open or closed elastic curve represented by a set of control points. Finding contours of distinct features (specified by the user *a priori* in an energy formulation) is done by deforming and moving the elastic curve gradually from an initial shape residing on the image toward the positions where distinct features are to be extracted. This deformation process is guided by iteratively searching for a nearby local minimum of an energy function, which consists of the internal energy (a smoothness constraint of the Snake curve: tension and bending) and the external energy that indicates the degree of matching for features (such as high image intensity for bright regions or large gradient strength for edges). This classical Snake model can be generalized to a three-dimensional (3-D) model and is known as the deformable surface model [13].

The geometric Snake model [4, 9] employs a geometric approach for the classical Snake and utilizes a level set approach for curve evolution [10, 11]. It was shown that the geometric Snake model performs better than the classical Snake model. Further improvement was done by providing the gradient of potential term of the classical Snake model into the geometric Snake model and is known as the geodesic active contours [5]. The basic concept of the geodesic active contours is that two-dimensional (2-D) object detection is based on computing paths of minimal weighted length. The geodesic active contours was shown to be better than both the classical Snake model and the geometric Snake model. This 2-D geodesic model was extended to a 3-D model by computing surfaces of minimal weighted area [6] and was implemented by the numerical algorithm for surface evolution via level sets [10, 11].

In general, the geodesic active contours were to find local minimal geodesics that are close to the initial guess. A global minimum Snake model [7] was proposed to find the minimal geodesics between two end points. This method is based on the interpretation of the Snake as a path of minimal cost. A numerical method was used to find the shortest path which is the global minimum of the energy among all paths joining the two end points. The advantages of the global minimum Snake model are easier Snake initialization and no trapping in a local minimum. In this paper, we extend this concept to three-dimensional object detection and apply to 3-D magnetic resonance (MR) image sequences.

Our goal in this study was to develop a computer algorithm to identify the inner and outer boundaries of the blood vessel wall in MR images. We based this algorithm on a 3-D Knowledge-based Global Minimum Snake (KBGM-Snake) model developed specifically for the various edge conditions found in MR images. The accuracy and reproducibility of this algorithm in measuring lumen and outer wall boundaries and total wall area was studied using in vivo MR images of human carotid arteries.

This paper is organized as follows: Section 2 describes a global minimum Snake model for three dimensional object detection. Section 3 presents the proposed KBGM-Snake algorithm. Simulation results are presented in Section 4, which is followed by the concluding remarks in Section 5.

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2. 3-D Global Minimum Snake Model

The Global Minimum technique was first introduced by Cohen and Kimmel [7]. This technique detects the global minimum of an active contour (Snake) model's energy between two points. This method finds a path of minimal cost in a Riemannian metric.

The concept of this Global Minimum technique can be extended to three dimensions (or two spatial dimensions plus time) by computing surfaces of minimal area. That is, given a potential function P, our goal is to find a surface along which the integration over P is minimal. The energy of the 3-D model has the following form:

$$E(S) = \iint_Q w\|\partial S/\partial a\|^2 + P(S(a))\, da$$

$$= wA(S) + \iint_Q P(S(a))\, da, \quad (1)$$

where S is a surface in R^3; Q is a bounded region in S; A is the area of the surface; w is a constant; and da is the element of area.

Now the minimization problem is to find the optimal surface that minimizes Eq. (1). For each point p, we first calculate the value of minimal action U_m that represents the minimal energy along the curve between p_m and p.

$$U_m(p) = \inf \{ \int_C P(C(s))\, ds \}, \quad (2)$$

where s is the arclength parameter; $C(L) = p$; and L is the length of the curve C.

For simplicity, we assume that the surface S is bounded by M points, $\{p_1, p_2, \ldots, p_M\}$ in R^3. Given the minimal action values U_n to p_n (where n = 1..M), the minimal surface bounded by p_n (i.e., $p_1, p_2, \ldots, p_M$) is the set of coordinate points $p_g = (x_g, y_g, z_g)$ that satisfy

$$\sum_{n=1}^{M} U_n(p_g) = \inf \{ \sum_{n=1}^{M} U_n(p) \}, p \in R^3, \quad (3)$$

Next, we need to determine the U value which can be found as solution of the Eikonal Equation.

$$\| \nabla U \| = P, \quad (4)$$

Sethian fast marching method [12] can then be used to solve Eq. (4). To calculate the U value in terms of 3-D coordinates, the numerical method approximating $U_{i,j,k}$ is extended from the 2-D case and is given by Eq. (5).

$$\begin{aligned} P^2_{i,j,k} = {} & (\max\{u - U_{i-1,j,k}, u - U_{i+1,j,k}, 0\})^2 \\ & + (\max\{u - U_{i,j-1,k}, u - U_{i,j+1,k}, 0\})^2 \\ & + (\max\{u - U_{i,j,k-1}, u - U_{i,j,k+1}, 0\})^2, \quad (5) \end{aligned}$$

where the potential values $P_{i,j,k} = P(i\Delta x, i\Delta y, i\Delta z)$ are on a grid and $\Delta x = \Delta y = \Delta z = 1$ for simplicity. Then Eq. (5) is solved for $U_{i,j,k}$ by selecting the largest u that satisfies Eq. (5).

Once the U value is available, the minimal surface of Eq. (3) can then be obtained by a simple steepest gradient descent method [7].

3. 3-D Knowledge-based Global Minimum Snake Algorithm

The KBGM-Snake algorithm was developed using Matlab (The Mathworks, Inc., Natick, MA.) on a SUN Sparc workstation designed to extract the lumen and vessel wall boundaries on MR images [14]. The KBGM-Snake algorithm can be described as follows:

The operator only needs to specify the center for the first image in a sequential series of images. Then the initial Snake points (i.e., end points) are detected by incorporating the knowledge about the intensity changes. There is a certain range of intensity between lumen and vessel wall, and between vessel wall and neighboring soft tissues. In our method, this knowledge is taken into account for the initial Snake points. This knowledge provides important guidance for intensity change when searching outward along a certain direction from the center.

Once the end points are selected, a Canny edge detector [3] is used to create a rough estimate of every possible edge contour within the image. This edge information is saved to a binary edge-detected map. Then the potential is formed as a function of the distance to the closest edge in the edge-detected map.

Then, the 3-D Global Minimum Snake model detects the global minimum of an active contour (Snake) model's energy for a series of images which represents a 3-D image data. This method interprets the Snake as an area of minimal cost. In our case, this area is bounded by two end points (p_1 and p_2) from location z - 1 and another two end points (p_3 and p_4) from location z. Therefore, the minimal surface bounded by p_1, p_2, p_3, and p_4 is the set of coordinate points p_g that satisfy

$$\sum_{n=1}^{4} U_n(p_g) = \inf \{ \sum_{n=1}^{4} U_n(p) \}, p \in R^3, \quad (6)$$

Based on the method discussed in the previous section, the energy function comes to rest at the minimal energy position, and the Snake curves fit closely to the luminal boundary.

The final step is supervised by the operator who may manually reposition any end points which have been positioned erroneously. The final Snake curves are then saved for future references. The luminal area is calculated by integrating the area within the luminal boundary contour. The outer wall area is calculated by integrating the area within the outer boundary contour of the vessel wall. The total wall area is calculated by subtracting the luminal area from the outer wall area.

4. SIMULATION RESULTS

MR images of human carotid arteries were acquired from a 1.5T whole body scanner (Signa, GE Medical System). A sequential series (14 serial locations) of carotid images were taken from five subjects. Figure 1 shows the Snake curve identifying the vessel boundaries in a series of one MR image.

To assess the accuracy of the KBGM-Snake algorithm, all calculated areas were compared with manually-traced boundaries. The manual tracing was conducted on the Independent Console (GE Medical System) by a reader blinded from the KBGM-Snake results. The statistical method described by Bland and Altman [1, 2] for comparing paired data was used to study the area differences between manual and computer measured data to determine if there is any 1) apparent bias by the KBGM-Snake algorithm, 2) significant differences, and 3) differences as a function of spatial location.

The results of using the Bland and Altman method are presented in Figure 2. The mean of the difference of wall areas was 0.3 mm^2 and the standard deviation of the difference was 3.5 mm^2. In comparison with the manual method, the percentage difference was about 2%. Figure 2 presents the Bland and Altman plots for the wall areas. As shown in Figure 2, the mean of the difference was small for these areas. In addition, the area difference distributed evenly and the standard deviation was relatively small. These results suggested that: 1) there was no systematic bias from using the KBGM-Snake algorithm, 2) there was strong agreement between the manual and the KBGM-Snake measurements as evidenced by the small standard deviations, and 3) there was no clear relationship between area difference (variance) and the size of the average area.

To evaluate the reproducibility of the KBGM-Snake algorithm, it was applied to a series of 14 images five times. The initial positions of the Snake points were changed prior to each application. The mean and standard deviation of the lumen, outer wall and total wall areas were calculated for each image. These results were then compared with those calculated using manually traced vessel boundaries. The manual tracing was performed over five consecutive days by the same reviewer with a custom made algorithm written in IDL (Research Systems, Inc.).

Figures 3 and 4 plot the mean areas and the standard deviation as determined by the KBGM-Snake and the manual boundary tracing algorithms, respectively. In general, both the KBGM-Snake and the manual mean and standard deviation plots show relatively small variances in wall areas. The KBGM-Snake numbers can be used as an estimate of both inter and intra viewer variability.

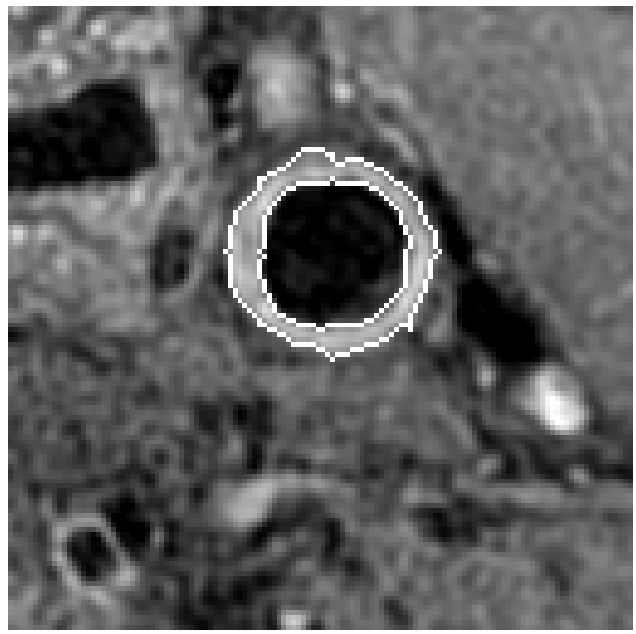

Figure 1: A sample of the Snake curve identifying the luminal boundary and outer wall boundary.

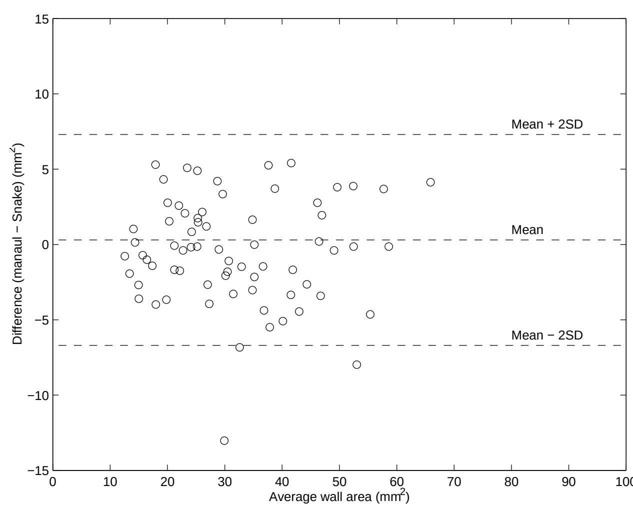

Figure 2: The Bland and Altman plot of the differences of wall areas measured manually and using the KBGM-Snake algorithm for all five subjects.

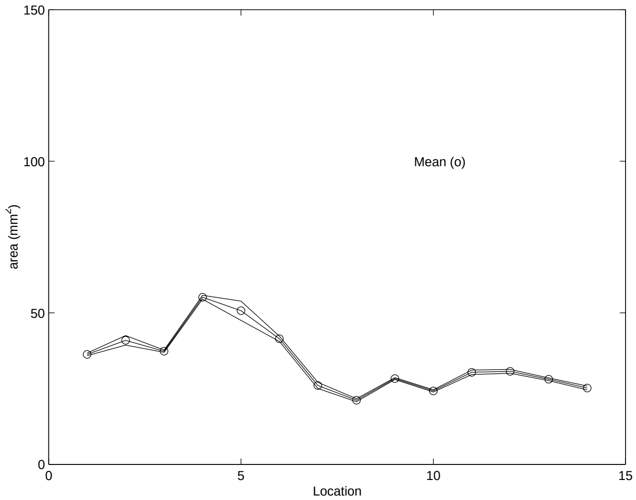

Figure 3: The mean and standard deviation of wall area measurements using the KBGM-Snake algorithm five times.

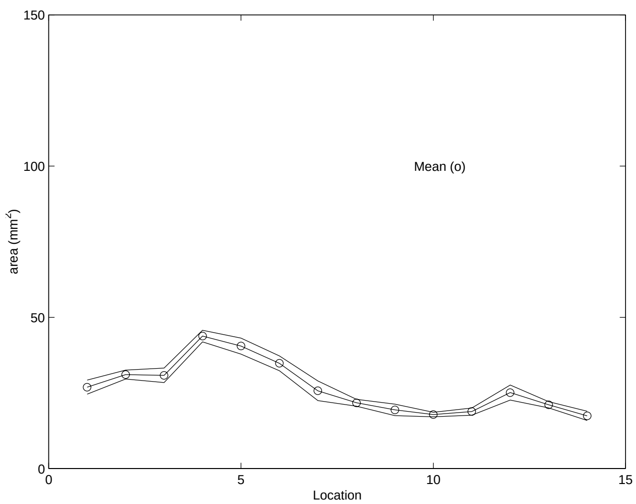

Figure 4: The mean and standard deviation of wall area measurements using a manual tracing algorithm five times.

5. CONCLUSION

Based on a 3-D global minimum Snake model, a KBGM-Snake algorithm was developed and applied to human carotid images for the purpose of identify the inner (lumen) and outer boundaries of the vessel wall. Area measurements were found to be accurate when compared to human manual area measurements and are highly reproducible.

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