User-Driven 3D Mesh Region Targeting

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Abstract

We present a method for the fast selection of a region on a 3D mesh using geometric information. This is done using a weighted arc length minimization with a conformal factor based on the mean curvature of the 3D surface. A careful analysis of the geometric estimation process enables our geometric curve shortening to use a reliable smooth estimate of curvature and its gradient. The result is a robust way for a user to easily interact with particular regions of a 3D mesh construed from medical imaging. We describe the applicability of the method for real-time clinician use.

In this study, we focus on building a robust and semi-automatic method for extracting selected folds on the cortical surface, specifically for isolating gyri by drawing a curve along the surrounding sulci. It is desirable to make this process semi-automatic because manually drawing a curve through the complex 3D mesh is extremely tedious, while automatic methods cannot realistically be expected to select the exact closed contour a user desires for a given dataset. In the technique described here, a user places a handful of seed points surrounding the gyri of interest; an initial curve is made from these points which then evolves to capture the region. We refer to this user-driven procedure as *targeting* or *selection* interchangeably.

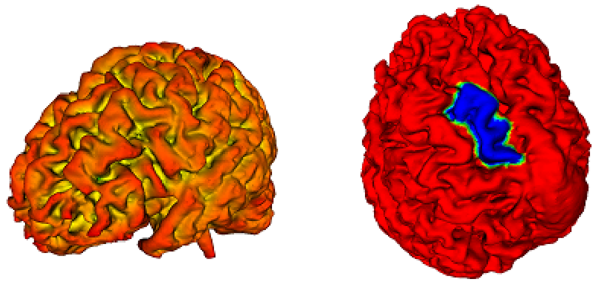
1 Description of Purpose

Many techniques have been devised for the structural segmentation of various anatomical features in medical imagery using 3D geometric information. Generally these fall into two broad categories. The first are the *automated* methods, where an algorithm must operate on an entire dataset without user interaction [1, 2]. The second group is that of *user-driven* methods, where some interaction is required to define parameters or initialization [3]. Our region selection method falls into the latter category, while the curvature estimation step could be applied to fully automatic algorithms that rely on curvature.

The existence of automatic feature extraction methods does not eliminate the need for user-driven algorithms. In automatic approaches, the problems are typically ill-posed and a reference truth doesn't exist. User-free Sulci extraction seeks to find as many curves as possible with minimal false positives; there is no guarantee that a particular region of interest would be selected. In contrast, user-driven methods use a minor initialization to make the problem well-posed and have a unique correct solution.

1.1 Our Contribution: New Work to be Presented

The contribution consists of two primary components. First, we make explicit the sources of difficulty in estimating surface curvature on a noisy mesh and present robust solutions to this problem. In particular, we make clear the necessity of proper neighborhood selection and regularized least squares for an accurate estimate of surface curvature gradient. Second, we introduce an energy formulation with a weighted arc-length minimization incorporating geometry of both the contour and the underlying surface. Unlike methods based on point-to-point minimal cost path computation [3, 4, 5], we do not need to constrain the initialization points to lie on the final path. The resulting selected region is consistent with respect to varying initialization points; accuracy is not degraded by suboptimally placed initial points. We will also show demonstrate the use of of the contour generation as a real-time feedback mechanism.



(a) (b)

Figure 1: Our technique operates on 3D triangulated mesh data by first robustly estimating the curvature, shown as a colormap in Fig. 1(a). This is a nontrivial step due to numerical instability and scale ambiguity. We then obtian several initialization points from a user to find a weighted minimal-length contour that selects a gyral region as in Fig. 1(b).

1.2 Originality

This work has not been published elsewhere, and it is not in submission or review currently.

2 Methods for Contour Selection Driven by Geometry Estimation

The goal of curve evolution for sulci targeting/selection is shown in Fig. 1. The curve is initialized with several seed points by the user and evolves according to the external force from the geometry of the surface and internal force from the geodesic curvature. After convergence, the curve should lie along a high outward surface mean-curvature groove. In the absence of such a maximally curved region the curve will simply shorten as much as possible. Unlike minimal-cost point-to-point path techniques, our approach does not fix the initialization points, so they do not have to be precisely placed by the user.

2.1 Regularized Surface Curvature Estimation

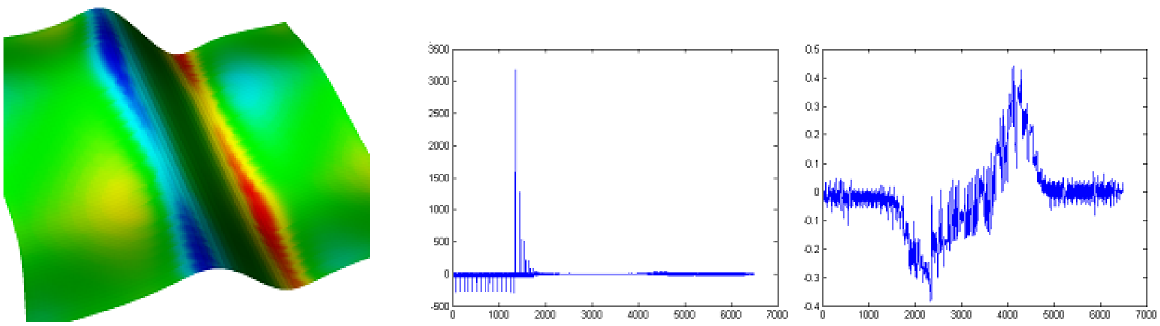
Estimates of the surface Mean and Gaussian curvatures are used in a variety of operations in medical image analysis (particularly registration and segmentation). However, the actual mechanics and numerical issues in computing them are not addressed as frequently in the literature as applications that assume an accurate geometric estimate as a precondition. The use of curvature is given slightly more explicity in [3], where it is computed with a quadratic surface fitting with 8-12 neighbor points. In our work it is clear that the data can have a profound effect on the results of geometry estimation with a fixed scheme, especially when we require third order derivatives (the surface gradient of curvature). Accurate and consistent results for data sets with varying resolution and quality can be achieved when the estimation process is properly designed.

2.2 Cost Functional and Associated Surface-Gradient Flow

We can now define a key concept of our work: a geodesic flow that captures sulci using geometric information.

Accordingly, let $\Gamma \subset \mathbf{R}^3$ be a smooth embedded compact surface, and let $\gamma : [0, T) \times \mathbf{R} \to \Gamma$ be an evolving family of curves. At any given time t we define the cost of the curve to be

$$\mathcal{C}[\gamma(t, \cdot)] = \int_{\gamma} e^{-\lambda H(\gamma(t,z))} \|\gamma_z(t, z)\| \; dz \tag{1}$$



(a) (b) (c)

Figure 2: A 3D surface that has locally nearly flat regions with slight additive noise Fig. 2(a), with smoothed regularized curvature estimate as colormap. A direct least-squares paraboloid fit leads to unstable per-vertex curvature estimates Fig. 2(b) that are beyond repair by mesh averaging. Our regularized curvature estimation creates curvature estimates that are quite useable for geometric techniques after a smoothing filter Fig. 2(c)

where $H : \Gamma \rightarrow \mathbf{R}$ is the outward mean curvature function on the surface. In this framework, for the brain *Sulci* are regions where $H \gg 0$, *gyri* are regions where $H \ll 0$. Curves with small cost will tend to be located in the sulci.

After computing the first variation, we obtain a steepest descent flow by choosing

$$v = \beta\left\{\kappa + \lambda N \cdot \nabla H\right\} \tag{2}$$

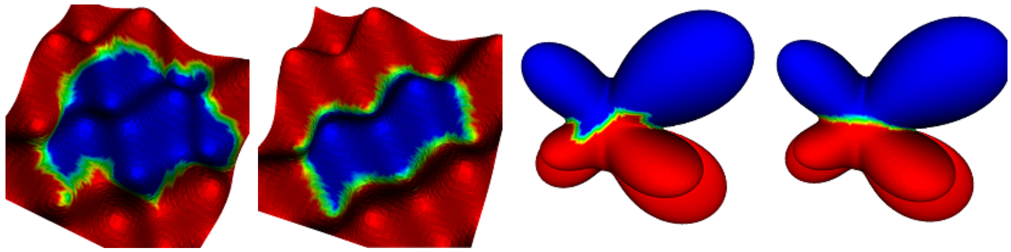
for some positive function β, which in implementation is chosen to satisfy stability requirements of the update scheme.

This scalar evolution rate is implemented as a level set flow on the surface. The theory of geometric curves on surfaces embedded in R^3 is detailed in [6].

3 Results and Conclusion

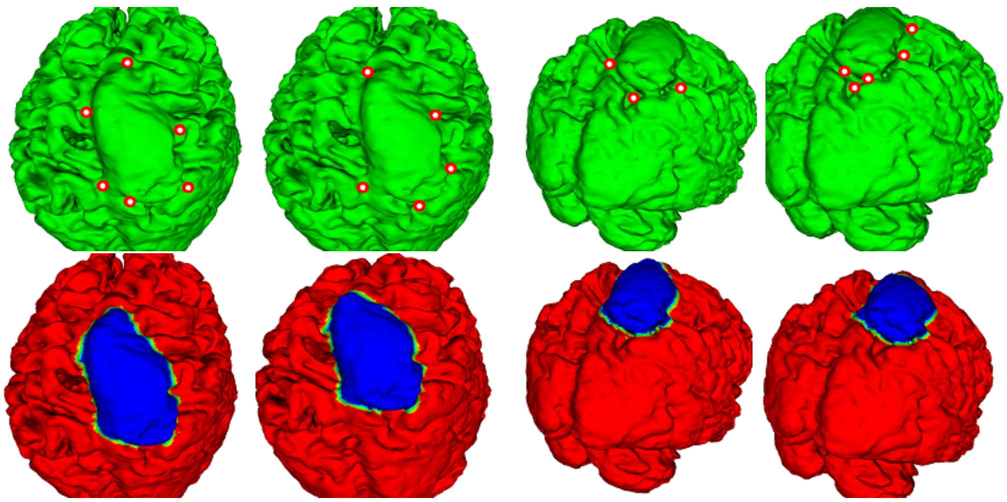
We implemented the techniques using VTK and C++, with the numerics of level set evolution using the Sparse Field Method [7]. The data sets used include several synthetic examples and MR brain imagery from Brigham and Women's Hospital that has been segmented and assembled into triangulated mesh data. Several initializations and results are shown in Fig. 3, Fig. 4.

Regularized curvature estimation is observed to be critical; without it, the cortical surface curvature estimates resemble Fig. 2(b) where noisy or nearly flat regions create numerical instability. Attempting to implement a geometric surface algorithm without a thorough understanding of the curvature numerics leads to disasterous numerical error. Regularization and use of real-world neighborhood scale allows the operating parameters to remain fixed, a vital requirement for usability. We also note that a curve on a mesh whose geometry is already computed can be updated in under 1 second, meaning that real-time clinician interaction is realistic.



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

Figure 3: Example results for two synthetic 3D objects. From intermediate contours 3(a) and 3(c) the final contours 3(b) and 3(d) are obtained.



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

Figure 4: Segmentation of a tumor on the right hemisphere of the cortical surface with four different initializations and the corresponding final contour.

References

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