Segmenting Cortical Structures by Globally Minimal Surfaces

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Abstract

In this paper we examine a new prospect for volumetric image segmentation, the globally minimal surface algorithm, and its application to segmenting anatomical structures in the brain. Existing minimal surface algorithms typically use a variational approach and so are prone to becoming stuck in local minima. The globally minimal surface algorithm used here is based on a maximal flow approach which has been mathematically proven to obtain optimal segmentations.

We present the application of globally minimal surfaces to segmenting a number of structures in the brain, as well as to tracking changes in the shape of the brain in a study of elderly patients. The results demonstrate that this new method is able to obtain robust and accurate segmentations with little user interaction. We conclude that a wide range of medical segmentation problems may benefit from the application of globally minimal surfaces.

1 Introduction

The segmentation of structures in the brain from magnetic resonance images is an important early stage in the quantitative analysis of a range of degenerative brain disorders. This is a challenging problem due to, on the one hand, the complicated shape of these structures and, on the other hand, the often poor contrast between tissues in the brain. As a result a range of segmentation methods have been proposed for this task with varying degrees of success.

Pham *et al.* [9] presented a complex segmentation method for reconstructing the cerebral cortex from magnetic resonance images. Their method consisted of several stages including tissue classification, masking of undesirable regions of the brain, topology correction and smoothing of the surfaces, and lastly a deformable surface driving the final result toward the cortex. Unfortunately the tissue classification suffered somewhat from noise, leading to poor results in successive stages. In addition the surface smoothing led in some cases to oversmoothing of the final result.

Wang *et al.* [11] investigated the measurement of volumetric changes in brain structures from magnetic resonance imaging. Their method was based on the classification of tissue types. This took into account partial volume effects, leading to a segmentation method with sub-pixel precision. They presented in [10] a validation of their methodology on a study of rates of brain atrophy in various stages of Alzheimer's, using normal elderly subjects for controls.

Goldenberg *et al.* [7] proposed a coupled geodesic active surface model in order to automatically extract the cortical gray matter boundaries in volumetric brain scans. They also presented an efficient numerical scheme to implement the coupled active surface model. The resulting segmentation method was successfully demonstrated on volumetric magnetic resonance images.

Unfortunately for methods based on the classification of tissue types such as [9, 11], local image information may be unreliable due to the presence of noise or irrelevant objects. This introduces errors into the classification which must be corrected by later stages. Filtering and geometric smoothing are common ways to reduce these errors after the fact however they reduce segmentation precision. Active contours and surfaces such as those used in [7] have been widely applied to image analysis and particularly to medical image segmentation. They are able to take into account basic geometric assumptions such as the expectation of surface regularity. However these methods are known to be difficult to initialise and often converge to an incorrect result without manual guidance.

In [3], Appleton *et al.* presented a novel approach to medical image segmentation, the globally minimal surface method. Globally minimal surfaces were proposed by Appleton and Talbot in [1] as an optimal form of geodesic active surface. They remove the dependence of geodesic active surfaces upon their initial configuration, leading to a reliable and robust segmentation method in practice. A mathematical proof of their optimality was included in this paper. A more extensive presentation of globally minimal surfaces is also given in [2]. Preprints of [2] and [3] may be obtained from the first author.

In this paper we will present the application of globally minimal surfaces to the segmentation of anatomical structures in 3D magnetic resonance images of the brain. Section 2 reviews the development of the globally minimal surface method, from the popular geodesic active contour segmentation energy through to a flow-based method which has been proven to obtain the optimal segmentation surface. Section 3 explains the practical application of the globally minimal surface method, including the selection of an appropriate *metric* as well as the placement of seeds to select the object to be segmented. Section 4 demonstrates the application of globally minimal surfaces to the segmentation of a number of physiological structures in the brain. In addition it presents a study into the changes in brain shape and volume of 8 elderly subjects over a 10 month period.

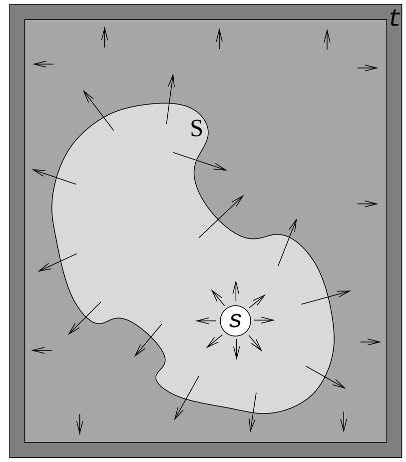

Figure 1. An example of the minimal surface – maximal flow duality in a two dimensional image. Arrows depict the flow $\vec{F}$ while the minimal surface S forms a bottleneck for the flow. The source s is a small region inside the object of interest while the sink t is the boundary of the image.

2 Globally minimal surfaces

2.1 Defining a surface energy for segmentation

Minimal surfaces were proposed for image segmentation by Caselles *et al.*, initially for two dimensional image segmentation as geodesic active contours [4], and later in three or more dimensions [5]. S is the segmentation surface, which is closed as it corresponds to the outline of an object being segmented. They are smooth closed surfaces which minimise the following energy function:

$$E[S] = \int_S g \mathrm{d}S \tag{1}$$

The *metric* g is a weighting function over the image domain which is obtained from local image information at each point. As the energy E is to be minimised, the metric should ideally be low on the boundaries of objects and high elsewhere.

Caselles *et al.* proposed to minimise this energy using a variational framework. Beginning with an initial surface, they evolved this surface by small deformations so as to successively lower the surface energy, halting at a local minimum. This surface evolution was implemented using a level set embedding, the details of which may be found in [4, 5] and a fast implementation in [6].

Minimal surfaces have proven to be popular in medical image segmentation where the objects under analysis tend to be smooth but may have widely varying shapes. Unfortunately the local minimisation proposed by Caselles *et al.* and in common use provides no guarantee on the quality of the final segmentation. This is because the energy described by Equation 1 is highly non-convex, containing many local minima which may trap the evolving surface. As a result minimal surfaces often require substantial user interaction in order to obtain good segmentations, which limits their practical application.

2.2 A maximum-flow formulation

In [1], Appleton and Talbot proposed a novel minimisation method for this problem. They observed that the minimisation of Equation 1 is dual to the maximisation of the following flow system:

- Conservation of flow: $\mathrm{div}\vec{F} = 0$.
- Capacity constraint: $|\vec{F}| \leq g$.

Here $\vec{F}$ is a vector field representing the velocity of an ideal fluid at every point in the image domain. Flow proceeds from one or more *sources* s inside the object of interest toward one or more *sinks* t outside of the object of interest. This is depicted in Figure 1. The speed of the flow is limited at each point by the metric g. As the flow is increased it is restricted by the metric, until a bottleneck forms which prevents any additional flow between the source and sink. Once this occurs the flow is maximal and the bottleneck is the globally minimal surface. This dual form of the minimal surface problem is convex, so that the maximisation of the net flow is very simple to achieve. For additional details regarding the maximum flow formulation and its numerical implementation, we refer the reader to [2].

3 Segmentation using globally minimal surfaces

In this section we show how to apply the globally minimal surface framework to image segmentation. This process consists of two parts: firstly the design of a suitable metric whose minimal surfaces will form good segmentation contours, and secondly the placement of internal and external seeds to select the objects to be segmented. Examples are presented at the end of this section.

3.1 Metric selection

As we seek to minimise the surface energy given in Equation 1, it is important that the metric g have low values on the boundary of the object to be segmented and relatively high values elsewhere. Object boundaries often exhibit an abrupt change in image intensity or in higher level features such as colour and texture. Therefore, in [4] Caselles *et al.* proposed the following image-based metric:

$$g = \frac{1}{1 + |\nabla G_\sigma \star I|} + \epsilon \qquad (2)$$

Here I is the image, $G_\sigma\star$ is the operation of convolution by a Gaussian of scale σ, and $|\nabla \cdot|$ computes the magnitude of the image gradient. ϵ is an additional parameter controlling the smoothness of the minimal surface. This was originally proposed for scalar images but may be extended to colour images or to texture analysis by extending the definition of the gradient operator $|\nabla \cdot|$ appropriately.

3.2 Seed placement

The globally minimal surface method requires the selection of both internal and external seeds. These seeds constrain the minimal surface to include some regions of the image and to exclude others. Typically the external seed is simply the boundary of the image while the internal seed is a small region inside the object to be segmented. However in complex segmentation problems we may place additional internal or external seeds to guide the segmentation surface where the correct object boundaries are ambiguous.

For 3D data it may be somewhat more complicated to place these seeds. To facilitate the segmentation of volumetric data we have designed a simple graphical user interface. This allows a user to navigate through a 3D dataset by viewing 2D slices. In addition it allows the placement of polyhedral seeds inside and outside of the object of interest. This user interface is described in more detail in [3] and may be downloaded for evaluation from [8].

3.3 Examples

Figure 2 depicts the segmentation of a cell in a histological section. Here it is only necessary to use a single internal seed to select this object. Note that despite the large amount of background clutter in the image, the globally minimal surface forms a good segmentation.

Figure 3 depicts the segmentation of an x-ray image of a clavicle. This is a more complex segmentation problem as several bones and a large screw have overlapped in the projection to film. As a result in this example it is necessary to use a number of internal seeds, guiding the globally minimal surface to include each part of the clavicle.

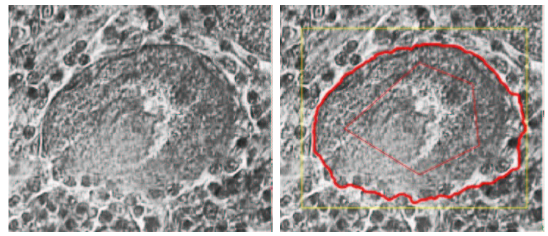

Figure 2. The segmentation of a cell in a histological section using a single internal seed.

4 Results

In this section we present the use of globally minimal surfaces to segment three structures in the brain: the lateral ventricles, the corpus callosum, and the hippocampi. Data consists of volumetric (3D) T1-weighted magnetic resonance images of the head. These segmentations are presented in order of increasing difficulty to demonstrate the new segmentation method over a range of problems. We then present the application of globally minimal surfaces in a study to track the changes in volume and shape of the brain in elderly subjects. This analysis may be used to quantify the progress of degenerative brain disorders such as Alzheimer's. Segmentations were performed on T1-weighted magnetic resonance images.

4.1 Segmenting cortical structures

The first and simplest segmentation is that of the lateral ventricles, depicted in Figure 4. This segmentation is relatively straightforward due to the simple shape of the ventricles as well as a clear intensity gradient on their boundary. A single internal seed was placed inside each of the two ventricles, while the external seed was simply the boundary of the volume.

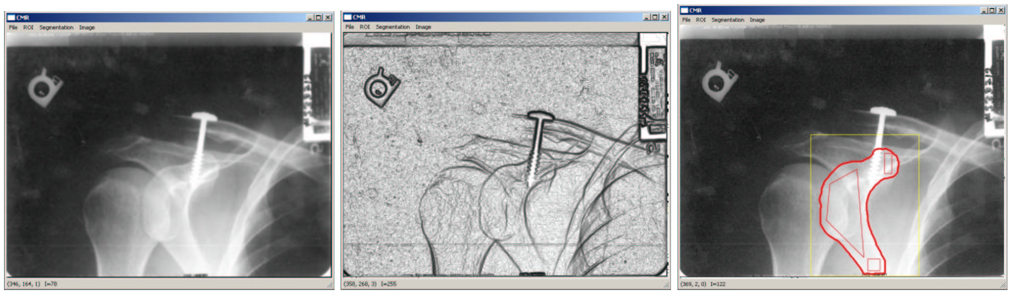

Figure 3. Segmentation of an x-ray image of a clavicle. Depicted in order: the original image, a gradient metric, and the resulting segmentation.

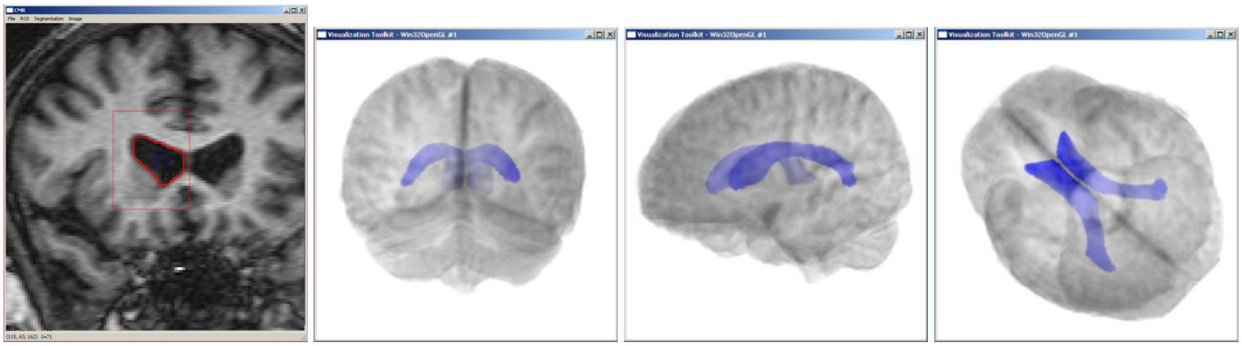

Figure 4. Segmentations of the lateral ventricles from a T1-weighted MRI dataset. Left: A 2D slice of the segmentation surface. Remainder: Different 3D views overlayed on the original data.

The second segmentation is a medial portion of the corpus callosum, depicted in Figure 5. The segmentation of the corpus callosum is more challenging than the segmentation of the lateral ventricles, as the boundary of the corpus callosum is obscured as the slices advance in a saggital aspect from the mid-plane of the brain. This segmentation required only a single internal seed, with the external seed being the boundary of the volume as before.

The third and most complex segmentation is that of the hippocampi, depicted in Figure 6. In this case the external seeds were bounding boxes for each hippocampus, while the internal seeds were line-like polyhedra following the centre lines of the hippocampi. The contrast in this segmentation is poorer due to the presence of some cerebro-spinal fluid (CSF) and white matter in adjacent to the hippocampi.

4.2 Tracking changes in shape

Due to degenerative diseases or simply as a consequence of aging a patient's brain may change shape over time. Locating and quantifying these changes may assist in the early diagnosis of degenerative diseases.

MRI datasets were taken from a large cohort in a comparative study into Alzheimer's disease and normal aging [11]. Eight data sets from eight elderly control subjects were used. Datasets consisted of two volumetric scans acquired from the same subject with 10 months separation. Each pair of datasets was co-registered prior to segmentation using a Euclidean (rigid body) transform. Following segmentation we may track changes in the shape of the brain according to the offset distance between the two snapshots.

Table 1 presents the differences in volume as well as the *similarity index* [12] of each subject's brain over the period of the study.

Figure 7 shows the changes to the brain in the 6th subject, who exhibited the greatest change in shape. Depicted are corresponding 2D slices which show that the most significant changes have taken place at the base of the brain. A surface offset map is also given showing areas of contraction (blue) and expansion (yellow). This analysis may be useful for locating particular areas of the brain which are atropying due to disease or expanding due to tumour growth for example.

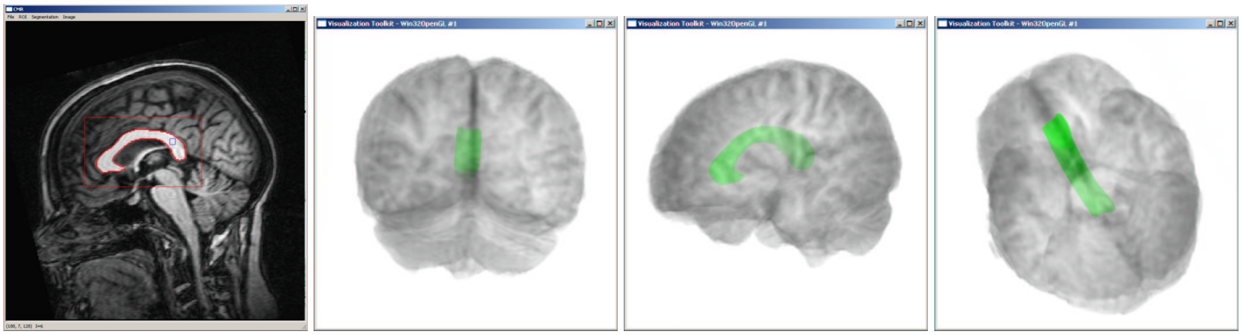

Figure 5. Segmentation of the corpus callosum from a T1-weighted MRI dataset. Left: A 2D slice of the segmentation surface. Remainder: Different 3D views overlayed on the original data.

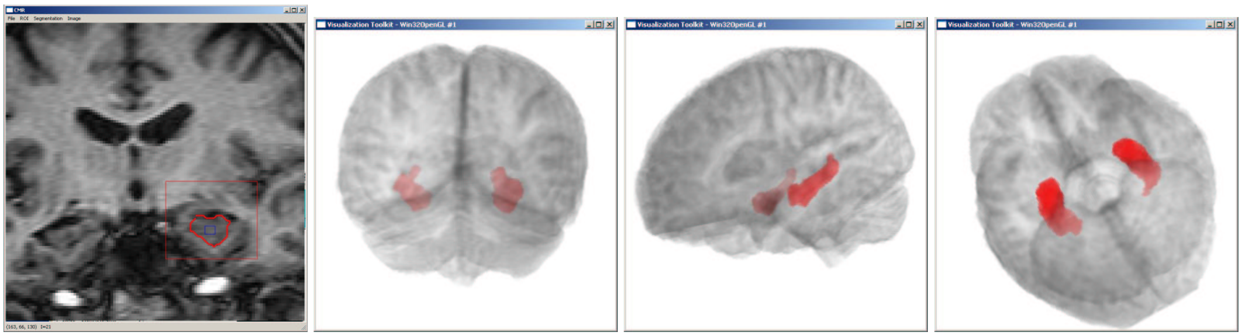

Figure 6. Segmentations of the hippocampi from a T1-weighted MRI dataset. Left: A 2D slice of the segmentation surface. Remainder: Different 3D views overlayed on the original data.

5 Conclusion

We have presented a new method for the segmentation of anatomical structures in the brain from magnetic resonance images. This method is based on the computation of a globally minimal surface according to a metric and a set of seeds. The metric is derived from the image data while the internal and external seeds select the object to be segmented and may also be used to fine-tune a segmentation. The globally minimal surface algorithm based on a maximal flow formulation is more robust than previous variational approaches such as level sets. Results have been presented demonstrating the application of this new method to segmenting a number of structures in the brain as well as to tracking changes in brain shape in elderly subjects. Based on these results, we suggest that globally minimal surfaces may be useful for a broad range of medical segmentation applications.

References

[1] B. Appleton and H. Talbot. Globally optimal surfaces by continuous maximal flows. In C. Sun, H. Talbot, S. Ourselin, and T. Adriaansen, editors, *Digital Image Computing: Techniques and Applications, Proc. VIIth APRS conference*, volume 2, pages 987–996, Sydney, December 2003. CSIRO publishing. Awarded best student paper prize.

[2] Ben Appleton and Hugues Talbot. Globally minimal surfaces by continuous maximal flows. *IEEE Trans. on PAMI*, 2004. Submitted.

[3] Benjamin C. Appleton, David N. R. McKinnon, and Deming Wang. Globally minimal surfaces for medical image segmentation. *Medical Image Analysis*, 2005. Submitted.

[4] V. Caselles, R. Kimmel, and G. Sapiro. Geodesic active contours. *IJCV*, 22(1):61–79, 1997.

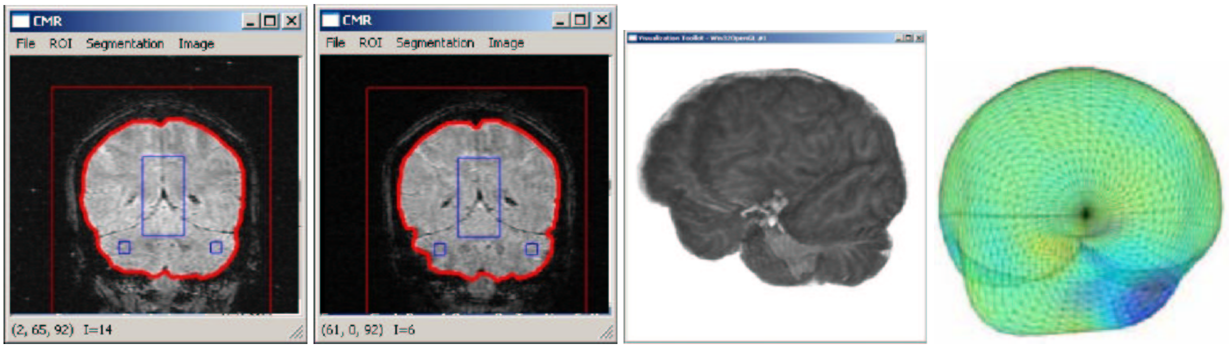

Figure 7. Tracking changes in the 6th dataset. Depicted in order: 2D slices of the segmentations at 10 months separation, a 3D view of the initial segmentation, and a surface offset map.

Subject	1	2	3	4	5	6	7	8	Mean
% Vol. diff.	1.34	0.42	0.02	0.58	2.00	2.92	0.66	0.19	0.91
Sim. index	0.986	0.983	0.985	0.989	0.984	0.981	0.989	0.988	0.986

Table 1. Tracking changes in brain volume and shape over a 10 month period in 8 subjects. Presented are the differences in volume in each subject's brain as well as the similarity index of its shape.

[5] Vicent Caselles, Ron Kimmel, Guillermo Sapiro, and Catalina Sbert. Minimal surfaces based object segmentation. *IEEE Trans. on PAMI*, 19:394–398, 1997.

[6] R. Goldenberg, R. Kimmel, E. Rivlin, and M. Rudzsky. Fast geodesic active contours. *IEEE Trans. On Image Processing*, 10(10):1467–1475, 2001.

[7] R. Goldenberg, R. Kimmel, and M. Rudzsky. Cortex segmentation - A fast variational geometric approach. *IEEE Trans. on Medical Imaging*, 21(2):1544–1551, Dec 2002.

[8] D. McKinnon and B. Appleton. CMR: Segmentation Application, 2004. http://itee.uq.edu.au/ mckinnon/cmr.

[9] D. L. Pham, X. Han, M. E. Rettmann, C. Xu, D. Tosun, S. Resnick, and J. L. Prince. New approaches for measuring changes in the cortical surface using an automatic reconstruction algorithm. In *SPIE Medical Imaging 2002 Conf.*, San Diego, CA, Feb 2002.

[10] D. M. Wang, J. B. Chalk, G. de Zubicaray, G. Cowin, G. J. Galloway, D. Barnes, D. Spooner, D. M. Doddrell, and J. Semple. MR image-based measurement of rates of change in volumes of brain structures Part II: Application to a study of Alzheimer's disease and normal ageing. *Magn. Reson. Imaging*, 20:41–47, 2002.

[11] D. M. Wang and D. M. Doddrell. MR image-based measurement of rates of change in volumes of brain structures Part I: Method and validation. *Magn. Reson. Imaging*, 20:27–40, 2002.

[12] A. P. Zijdenbos, B. M. Dawant, R. A. Margolin, and A. C. Palmer. Morphologic analysis of white matter lesions in MR images: method and validation. *IEEE Transactions on Medical Imaging*, 13(4):716–724, December 1994.