Cellular Complexes: A Tool For 3d Homotopic Segmentation In Brain Images

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Abstract

Cortex surface modeling is important in several domains including for solving the inverse problem in EEG and MEG. Whereas MRI can be used to build such a model, problems arise due to the partial volume effect that makes the cortex surface disappear in the foldings.

To solve this problem we use a model, based on cellular complexes, that has good topological properties. This model allows to represent any object which is the combination of volumes, surfaces and curves in a discrete space. We define homotopic deformations on such a model by adapting the notion of simple points to our model.

We use this homotopic deformable model to segment the cortex surface and to preserve the spheric topology of the surface during the deformation process. The model is initialized from the external brain surface and is then deformed towards the minimum value of an energy function that pushes the surface inside the foldings.

1 Introduction

Magnetic Resonance Imaging (MRI) can be used to build models of head structures (brain, skull, scalp, etc.). These models are important in several domains, including for solving the inverse problem in MEG and EEG [2, 4, 8]. The cortex is of great importance in this problem and to have a good representation of the cortex surface is necessary. Problems arise due to the cortical topology and the high inter-individual variability [7]. The cortical ribbon presents a lot of foldings and on MRI images the cortex surface disappear in the foldings because of partial volume effect (figure 1b). This makes the surface segmentation a difficult problem.

To solve this problem we introduce a new model that allows for the representation of structures thinner than the voxels. This model is based on cellular complexes and is presented in section 2. Then we show that we can use homotopic deformations on such a model. This is applied to the segmentation of the cortex surface from 3D MR images in section 3, where an initial surface represented according to this model is deformed towards the desired result by preserving homotopic properties.

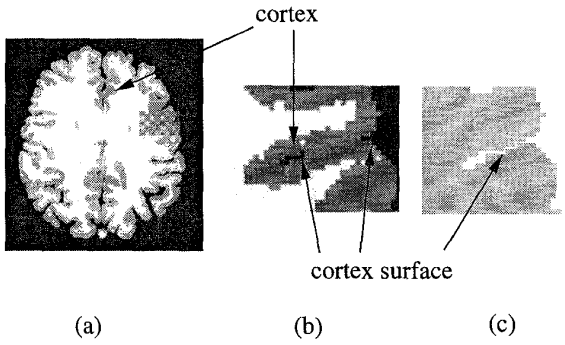

Figure 1: Representation of thin surfaces: (a) Segmented and classified brain image (b) Zoom on the grayed part (c) Brain volume without the cortex surface.

2 Cellular complex as a basis for deformable model

The need to introduce structures thinner than the voxels in an image and the necessity to work on a space with good topological properties can be solved simultaneously and integrated in one model. The modeling of an image based on cellular complexes [6] allows the representation of any object that is the combination of volumes, surfaces and curves in a discrete space, and avoids the well-known connectivity paradox.

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2.1 Cellular complexes

To avoid the *connectivity paradox* in 3D images we need a new structure with good topological properties. Kovalevsky [6] proved that every finite topological structure is an abstract cellular complex. He introduced a new representation of images based on cellular complexes and free from topology paradoxes. This is the representation we will use for modeling the cortex.

In 3-dimensional binary images a scene is represented by two sets of voxels O and $\overline{O}$, the first one containing the *object points* the second constituted of *background points*. To use a new representation that is close to the original rectangular grid and free from topological paradoxes, we represent the set E of all the elements that are an intersection of two voxels. We have four types of elements in E called *cells*: cubes, faces, edges and points. The dimension $dim(c)$ of a cell is 3 (resp. 2, 1, 0) for cubes (resp. faces, edges, points). The cells are linked with a *connectivity relation* $f_E \subset E \times E$ such that $(c', c'') \in f_E \iff c' \cap c'' \neq \emptyset$ and $dim(c') \neq dim(c'')$. For example a face has ten neighbours: two cubes, four lines and four points (figure 2).

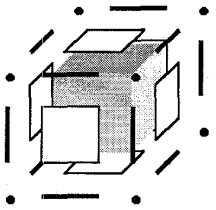


Figure 2: The different cells constituting the cellular complexe.

It is now possible to represent thin structures such as the cortex surface (figure 1c) and to use the good topological properties of the model to define homotopic deformations.

2.2 Homotopic deformations

There is no unique definition of deformations that preserve topology in the literature. In the discrete 3D topology framework, this notion is usually defined as the preservation of *connected components* and *tunnels* of both the object and the background [5, 9]. Tunnels are characterized according to the notion of continuous deformation of loops (i.e closed path). There is a tunnel into an object if it exists a loop in the object that cannot be continuously deformed in a point without crossing the background. For example a sphere has no tunnel and a torus has one tunnel. Continuous deformation of loops is an equivalence relation. The *number of tunnels* is the number of equivalence class of unreductible loops.

For classical images, it is necessary to adapt the notion of continuous deformation to the discrete case. This leads to a local characterization of *simple points* that are the points that can be removed from the object without changing the topology [1].

The local characterization allows fast computation of simple points and can be used for homotopic deformations [7]. In order to adapt the notion of simple points to cellular complex we introduce the *simple cells*. A cell is simple if and only if it can be removed without changing the topology (i.e. number of connected components and number of tunnels) of the object nor the topology of the background. We show in section 2.3 that the notion of simple cell depends only on the cell neighborhood and therefore can be used iteratively to deform the whole model.

2.3 Deformation of a cellular complex based model

In order to define homotopic deformation for our model, we need to adapt the notion of path and continuous path deformation. A path on a cellular complex is a sequence $s_1, s_2, ..., s_N$ of cells where s_i and s_{i+1} are neighbors. The notion of *deformation* for a path is based on notion of *elementary deformation* of a path. A path deformation is a sequence of elementary deformations that are applied to the path. In order to define an elementary path deformation for our model, we uses the fact that there are only four different configurations of three cells that are mutually neighbor (figure 3). In these configurations any cell can be continuously deformed towards the union of the two others. Therefore if it exists two paths $\Gamma = \gamma_1.s1.s2.s3.\gamma_2$ and $\Gamma' = \gamma_1.s1.s3.\gamma_2$ where γ_1 and γ_2 are paths and s_1, s_2, s_3 are mutually neighbors, then the object composed by the cells of Γ can be continuously deform in the object composed of the cells of Γ'.

Therefore, a path deformation is a continuous deformation that is used to define loop deformation. Hence, the definition of the number of tunnels and of homotopy are similar to the continuous case.

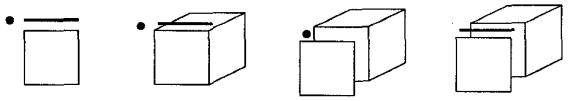


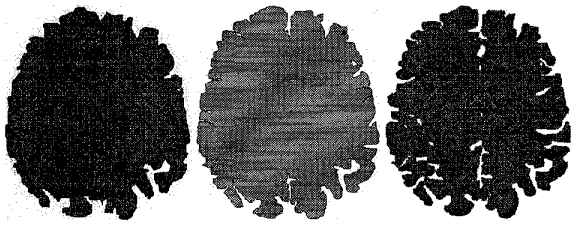
Figure 3: Four configurations of mutually neighbor cells.

Starting from the definition of homotopic deformation for cellular complex based models we proved that

the *simple cells* can be locally characterized. A cell is simple if and only if his neighborhood contains exactly two connected components, one for the object and one for the background. This local property is easy to compute and can be used to remove (resp. add) cells from (resp. to) the model without changing its topology. By iteratively removing or adding simple cells, we obtain an homotopic deformation of a cellular complex based model.

3 Segmentation of the cortex surface

To segment the surface of the cortex we initialize a cellular based deformable model on the external brain surface (figure 4a). This model is then deformed by iterative removing of simple cells towards the inner part of the cortex gyri (figure 4b and 4c).



(a) (b) (c)

Figure 4: (a) Initial model, (b) Intermediate step, (c) Final segmentation.

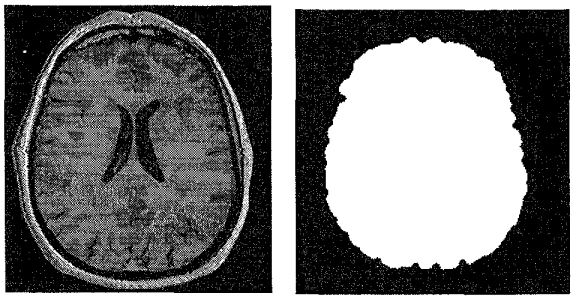
3.1 Initialization of the model

To extract the brain from MR images, we use the method proposed by Geraud [3]. This method is based on mathematical morphology operators. The result is a binary image of the brain (figure 5). To initialize the model we must decide which cells are part of the object and which are part of the background. We set all the cubes according to the corresponding voxel in the mask. Any other cell (face, edge or point) is part of the object if and only if an object cube belongs to its neighborhood.

3.2 Guiding the deformations

In order to guide our deformable model from the outer brain surface toward the inside of the cortex gyri, we make a few assumptions about the cortex:

- The cortex has a spherical topology. This important assumption allows us to limit the possible deformations of our model. The spherical topology is imposed by the brain segmentation process and preserved during the deformations.
- The cortex width is almost constant. This assumption is important to be able to detect the cortex surface where it is not seen in the image because of partial volume effect. If we suppose that the cortex width is equal to cw (about 3mm), we can say that in the place where the cortex surface could be, there must be a cortex structure of size $2*cw$ (figure 8). To use this property to guide our model, we must be able to detect the cortex location. This is done with an image that gives, for each voxel, a membership value to the cortex. To build this image, we perform a classification of the brain image with the k-means algorithm, then we extract the cortex label and apply a mean filter to account for imprecision on the cortex delination (figure 6).



(a) (b)

Figure 5: (a) Initial MR image, (b) Brainmask. (shown on one slide of the 3D volume).

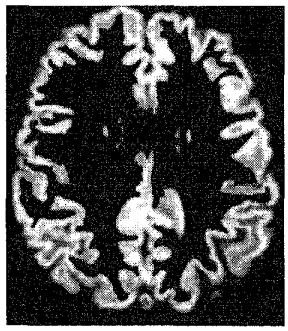


Figure 6: Membership to the cortex (μ_{cortex}).

- The location of the cerebrospinal fluid (csf) inside the brain is a good indicator of the cortex surface location. The brain is immersed into the csf and the csf goes into the cortex gyri. Therefore, we can use the csf inside the gyri to guide our model. The location of the csf can be computed with mathematical morphology using watershed [3] (figure 7).

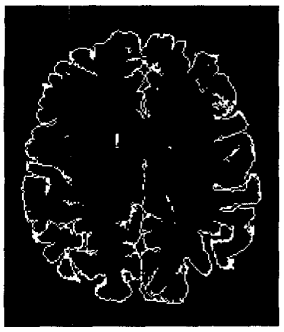


Figure 7: Cerebrospinal fluid location (μ_{csf}).

3.3 Segmentation algorithm

To deform our model, we must choose, among the simple cells, which ones can be removed to push the model towards the gyri. These cells are then removed and the process is iterated until there is no more cell to remove. Since there is a finite number of cells the algorithm always terminates. But it could be very long because the number of cells is important and, in order to preserve the topology, only a small number of cells are removed on each iteration. The way we decide to remove a simple cell s is different according to its dimension :

- If s is a line or a point it is only used for topology preservation. So s is removed if it cannot generate a long 1D structure (i.e. containing more than two lines).
- If s is a cube it is removed if its membership to the cortex is too low (i.e. $\mu_{cortex}(s) < t_{cortex}$ where t_{cortex} is a parameter of the algorithm). In this way we dig into our model where the gyri are large enough to avoid partial volume effect.
- If s is a face, it is removed according to the assumptions we have done before about the cortex. These hypotheses are expressed as cost functions that are combined together in a final cost function $C(s)$. Except the topology, we have two hypotheses about the cortex, which are represented by the two functions $C_{cortex}(s)$ and $C_{csf}(s)$:
  - $C_{cortex}(s)$ represents the assumption that the cortex width cw is constant. cw is a parameter of the algorithm. Therefore, we need to verify that there is enough grey matter on both sides of the face s. This is achieved by computing the average μ_{cortex} on a distance cw on both sides of the face (figure 8).

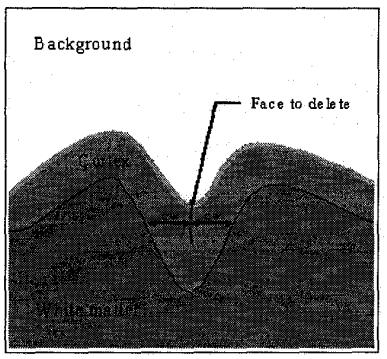


Figure 8: Verification that the face to delete is on the cortex surface according to the cortex width.

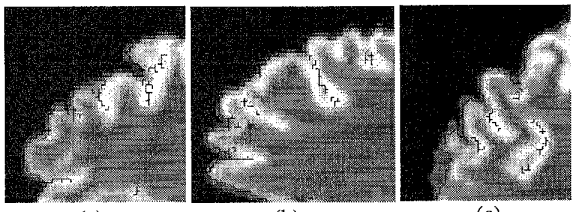
  - $C_{csf}(s)$ is used to guide our model with the location of the csf, we compute it as the mean value of μ_{csf} of the two cubes that are neighbors of s.

$C_{cortex}(s)$ and $C_{csf}(s)$ are combined in the final cost function $C(s)$ according to a weight parameter w: $C(s) = w.C_{cortex}(s) + (1 - w).C_{csf}(s)$. The face is removed if $C(s) > t_{cost}$ where t_{cost} is a parameter of the algorithm.

3.4 Results

The figure 9 shows the result of the segmentation algorithm on a subpart of the cortex. It displays the membership to the cortex superimposed with the border of the final model (in dark lines). On these images we show only the faces of the border that are perpendicular to the view plane. The border of the model seems to be in several pieces but it is not the case, the whole border is 3D connected and topologically equivalent to a sphere.

The model has been succesfully guided towards the desired result. Both the constant cortex width and the csf location assumptions are necessary to have a good segmentation. The choice of the parameters was empiric. The most difficult parameter to choose is the threshold of the cost functions, it represent a compromise between the quality (smoothness) of the surface and the amount of gyri detected. The location of the final surface in the gyri is good. However, when the cortex structures are too large (according to cw), the surface presents two or more parallel parts (see on the upper-right of figure 9b). On the other hand, when the structures are too small they are not detected. The errors of detection in the large structure could be



(a) (b) (c)

Figure 9: Final segmentation. Zoom on three orthogonal slices. (a) coronal, (b) sagital, (c) axial.

avoided by the introduction of a cost function based on the proximity of the inner parts of the surface.

The resulting surface is not smooth. This is because we do not impose any intrinsic regularisation on the surface exept the topology preservation. To avoid this it is possible to add cost functions based on the surface normals or curvatures. This is left for future work.

3.5 Conclusion

The cellular complex based deformable model is an original tool for image processing. It can be used for all the applications that need to represent objects that are composed of truly 2D surfaces mixed with volumes. The good topological properties of the model allows to easily deform it according to intrinsic criteria (topology, curvature, etc.) as well as to image processing based criteria.

This model has been used for the segmentation of the cortex surface. In this case the topology of the cortex is know a priori and can be preserved during the deformation process. The ability to have surfaces and volumes in the same model has been used to represent the cortex surface inside the gyri.

Our future work will be to add some regularization cost functions to make the detected surface smoother. This functions will be based on the approximate calculation of the normals and curvatures of the surface. The final result will be used to build a current sources model for solving the inverse problem in EEG/MEG.

References

[1] Gilles Bertrand and Grégoire Malandain. A new characterization of three-dimensional simple points. *Pattern Recognition Letters*, 15:169–175, February 1994.

[2] Anders M. Dale and Martin I. Sereno. Improved localization of cortical activity by combining eeg and meg with mri cortical surface reconstruction: A linear approach. *Journal of Cognitive Neuroscience*, 5(2):162–176, 1993.

[3] Thierry Geraud. *Segmentation automatique des structures cérébrales internes en imagerie par résonance magnétique tridimensionnelle.* PhD thesis, Ecole Nationale Supérieure des Télécommunications, June 1998.

[4] Matti Hämäläinen, Riitta Hari, Risto J. Ilmoniemi, Jukka Knuutila, and Olli V. Lounasmaa. Magnetoencephalography theory, instrumentation and applications to noninvasive studies of the working human brain. *Reviews of Modern Physics*, 65(2):413–497, April 1993.

[5] T. Y. Kong and A. Rozenfeld. Digital topology: Introduction and survey. *Computer Vision, Graphics, and Image Processing*, 48:357–393, 1989.

[6] V. A. Kovalevsky. Finite topology as applied ti image analysis. *Computer Vision, Graphics, and Image Processing*, 46:141–146, 1989.

[7] Jean-François Mangin. *Mise en correspondance d'images médicales 3D multi-modalités multi-individus pour la corrélation anatomo-fonctionnelle cérébrale.* PhD thesis, Ecole Nationale Supérieure des Télécommunications, March 1995.

[8] Bernard Renault and Line Garnero. L'imagerie electromagnétique cérébrale, principe de base et perspectives. *Colloque de l'Académie des Sciences: Instrumentation physique en biologie et en médecine*, pages 131–139, December 1994.

[9] Y. F. Tsao and K. S. Fu. A parallel thinning algorithm for 3-d pictures. *Computer Vision, Graphics, and Image Processing*, 17:315–331, 1981.