Multilabel, Multiscale Topological Transformation for Cerebral MRI Segmentation Post-processing

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Abstract. Accurate segmentation of cerebral structures remains, after two decades of research, a complex task. In particular, obtaining satisfactory results in terms of topology, in addition to quantitative and geometrically correct properties is still an ongoing issue. In this paper, we investigate how recent advances in multilabel topology and homotopy-type preserving transformations can be involved in the development of multiscale topological modelling of brain structures, and topology-based post-processing of segmentation maps of brain MR images. In this context, a preliminary study and a proof-of-concept are presented.

Keywords: Homotopic deformation · Multilabel topology ·
Multiscale modelling · Segmentation · MRI · Brain

1 Introduction

Topological methods generate a growing interest in the field of medical image processing and analysis. Indeed, ensuring the coherence of structural properties of the organs and tissues in 3D medical data is a cornerstone e.g. for registration, modelling or visualization tasks. In particular, topological concepts developed in the field of discrete imagery, and in particular digital topology, can allow for the development of efficient approaches that take into account not only quantitative and morphometric information carried by anatomical objects of interest, but also more intrinsic properties related to their structure [21].

In particular, the brain has received a specific attention. Indeed, by contrast with other organs, it exhibits an important interindividual variability from shape and size points of view. In the meantime, it is organized into many distinct subparts and tissues with a strong topological invariance. Taking into account

topological priors is then a relevant hypothesis for guiding and/or regularizing image processing procedures [19].

This article presents a contribution in the field of topology-based brain structure segmentation. More especially, we focus on topological post-processing of multi-label segmentation maps obtained beforehand with efficient, but non-topologically guided, methods. Our purpose is then to build, from such segmentation maps, a corrected output consolidated by topological priors.

This research area is not new; related works are recalled in Sect. 2. However, the embedding of topological priors in segmentation paradigms is a complex task, a fortiori when we consider n-ary segmentation, with $n > 2$, i.e. more than one object vs. its background. In this context, our contributions are the following. First, we rely on a topological framework introduced a few years ago by some of the authors, that allows to correctly model digital images by considering the topology of n labels but also that of the combinations within their power lattice [16,18]. Second, we consider a multiscale approach for topological modelling of the cerebral structures. Indeed, we assume that the topological assumptions that should guide a segmentation process actually depend on the level of details of the observed structures. Based on these two, multilabel and multiscale, paradigms, we develop a generic, homotopic deformable model methodology that progressively refines a segmentation map with respect to the data and the associated topological priors.

In Sect. 3, we recall the involved topological framework and how it can be used for multiscale, multilabel topological modelling of anatomical structures. In Sect. 4, we describe the algorithmic scheme that allows us to progressively refine an initial segmentation with respect to this multiscale topological modelling. Experimental results are proposed in Sect. 5; at this stage, they have mainly an illustrative value. Section 6 concludes this article by presenting the main perspectives offered by the proposed approach and the remaining challenges to be tackled.

2   Related Works

Topology-based segmentation methods dedicated to brain structures can be mainly divided into two families [19]: on the one hand, the methods that consider a topological prior for guidance from the very beginning of the process; on the other hand, the methods that aim at recovering a posteriori some correct topological properties. The first lie in the family of topological deformable models; the second in the family of topological correction methods.

In most of these methods, the considered structures of interest are the main three classes of tissues, namely grey matter (GM) (mainly, the cortex), white matter (WM), and cerebrospinal fluid (CSF). A majority of the proposed methods focus on the cortex, that presents a complex geometry, with strong folding and a low thickness, leading to a high curvature 2D-like thin ribbon. Cortex segmentation is generally presented as a binary segmentation problem (cortex vs. other structures) or a ternary segmentation problem (GM, WM, CSF).

The associated topological hypotheses are often a simplified version of the anatomical reality, and the different classes of tissues are assumed nested: the central class is simply connected (i.e. a full sphere) with successively nested hollow spheres. Based on these simplified assumptions, it is possible to develop segmentation strategies from binary digital topology [13], and in particular homotopic transformations based on simple points [8] (less frequently, alternative topological models were proposed, for instance cellular complexes [7,9]).

Since the pioneering works proposed in [15], different variants of such topological deformable models have been proposed, in fully discrete paradigms [5] or by coupling continuous and digital models [11]. However, the hard topological constraints imposed by the model can lead to deadlocks that are difficult to handle (see [10] for a discussion on that topic). Based on the same topological hypotheses, many topology correction methods have been proposed for the cortex. They mainly consist of identifying the tunnels/handles generated on the cortical surface, and removing them based on ad hoc strategies [3,14]. These methods aim at reformulating the topological problem to be solved by considering a binary, simply connected topological model, which has the virtue to be easy to handle, but the drawback of poorly modelling the anatomical structures.

More recently, new ways were explored for tackling the issue of real multilabel segmentation and/or potentially complex topologies. Handling complex topology can be done by relying on less constraining—but also less robust—topological invariants, such as the genus [22]. Homotopic transformations based on simple points however remain the gold standard for carrying out model transformation. In order to avoid topological deadlocks, non-monotonic transformation processes of complex, multilabel topological models were investigated [4,20]. Although promising, these approaches suffer from various theoretical weaknesses [2,20,23] (see [18] for a discussion). They also work at a unique scale, with induced difficulties to ensure simultaneously spatial/geometrical and topological reliability.

3   Multilabel, Multiscale Topological Modelling

3.1   Theory

In [16], Mazo proposed a framework for modelling the topology of multilabel digital images. The main ideas of this framework are as follows.

1. The multilabel image is splitted in a collection of binary images such that each binary image represents a region of interest, that is a region that has been previously labelled or represents a meaningful union of some labeled regions. The unions are labeled thanks to a lattice structure: the label of a union of regions is the supremum of the labels of the regions.
2. Each binary digital image is embedded in a partially ordered set (poset) by adding intervoxels elements (pointels, linels, surfels). Such elements are assigned to the foreground or the background thanks to the minimum (6-adjacency) or maximum (26-adjacency) membership rule. Doing so, the connected components are preserved and the digital fundamental groups, as

defined by Kong [12], are mapped, through isomorphisms, to the fundamental groups of the Alexandrov topology [17].
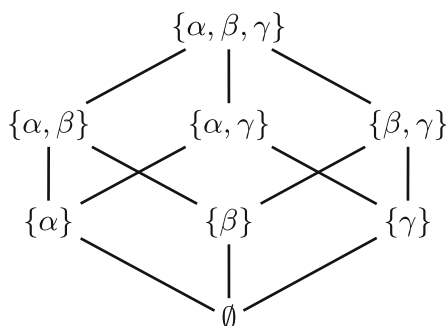

Fig. 1. The power lattice $\Lambda = 2^L$ for the set of labels $L = \{\alpha, \beta, \gamma\}$ of the three considered classes of cerebral tissues.

In this framework, a homotopic relabelling boils down to a collection of simple point moves in binary images with the guarantee to preserve the underlying topological structures of the involved posets, and in particular their homotopy-types.

3.2   Application

In the applicative context of this work, our purpose is to post-process ternary classification maps of MR images defined as

$$\left| \begin{array}{l} F : \Omega \to [0,1]^3 \\ \quad x \mapsto (p_{\mathrm{CSF}}, p_{\mathrm{GM}}, p_{\mathrm{WM}}) \end{array} \right. \tag{1}$$

where Ω is a part of $\mathbb{Z}^3$ corresponding to the support of an MR image, and for each point x, p_{CSF}, p_{GM} and p_{WM} are the probabilities that x belong to the cerebrospinal fluid, the grey matter (cortex) and the white matter, respectively. In particular, we have $\sum_\ell p_\ell = 1$.

Such maps F are obtained by a fuzzy segmentation process described in [24] (but they may be obtained via any other similar segmentation procedure, e.g. [6]). A specificity of this segmentation strategy—and many others—despite its good accuracy from quantitative and geometric points of view, lies in the fact that it is not guided by topological constraints. As a consequence, its output needs to be post-processed for any further application requiring topological guarantees (for instance mesh generation or differential cortical surface analysis).

Our purpose is then to build, from F, a new crisp segmentation map

$$\left| \begin{array}{l} T : \Omega \to \{0,1\}^3 \\ \quad x \mapsto (c_{CSF}, c_{GM}, c_{WM}) \end{array} \right. \tag{2}$$

such that for each point x, c_{CSF}, c_{GM} and c_{WM} are equal to either 0 or 1 depending on the (unique) class of x, i.e. with $\sum_\ell c_\ell = 1$.

In addition, T should satisfy—unlike F—some topological priors related to the structure of the different tissues.

3.3 Multiscale Topological Modelling

The framework proposed in [16] allows us to model the topological structure of the three classes of cerebral tissues of interest, namely CSF, GM and WM, further noted γ, β and α, respectively, for the sake of concision. It also allows us to model any combinations of these labels, leading to the whole power lattice $\Lambda = 2^L$; see Fig. 1.

In particular, in [16], the notion of topology preservation relies on the definition of simple points that preserve the homotopy-type of *all* the labels of Λ. However, it is possible to consider the notion of simpleness for only a given (strict) subset of labels of Λ. In such a case, it is sufficient to guarantee that the relabelling of a (simple) point fulfills the required topological conditions for the chosen subset of labels, while the topology of the objects/complexes induced by the other labels are allowed to evolve.

This strategy, that only focuses on specific (combinations of) labels of interest, permits to define a multiscale topological modelling. Indeed, the notion of topology in discrete imaging is strongly related to the scale of observation of the objects of interest. For instance, fine topological details that are relevant at a high resolution, become useless (and sometimes incorrect) at a coarser resolution, due to the loss of precision induced by partial volume effects.

Based on this assumption, we consider two distinct topological models of the brain tissues, according to their scale (see Fig. 2):

– **Model 1 – Coarse/intermediate scales ($\mathbf{S_1}$ and $\mathbf{S_2}$):** At these scales, we assume that the WM, GM and CSF are successively nested, which is the hypothesis currently considered in the literature. In other words, we aim at preserving the homotopy-type of three labels: $\{\alpha\}$ (simply connected); $\{\beta\}$ (hollow sphere); and γ (hollow sphere); but also the homotopy-type of their four combinations.
– **Model 2 – intermediate/fine scales ($\mathbf{S_2}$ and $\mathbf{S_3}$):** At these scales, we assume that the cortex (GM) is no longer a hollow sphere. Indeed, on the lower part of the encephalus, the hypothesis of GM surrounding WM is not satisfied (due to the connection of the encephalus to the brainstem). Based on this hypothesis, we aim at preserving the homotopy-type of five labels: $\{\alpha\}$ (simply connected); $\{\alpha, \beta\}$ (simply connected); $\{\beta, \gamma\}$ (hollow sphere); $\{\gamma\}$ (hollow sphere); and $\{\alpha, \beta, \gamma\}$ (simply connected). In particular, this allows to make the topology of the cortex evolve whereas remaining coherent with respect to its neighbouring structures (CSF and WM).

4 Multilabel, Multiscale Topology-Controlled Deformation

We now describe how the topological assumptions modeled above can be considered for designing, at each scale, well-fitted homotopy-type preserving deformation processes.
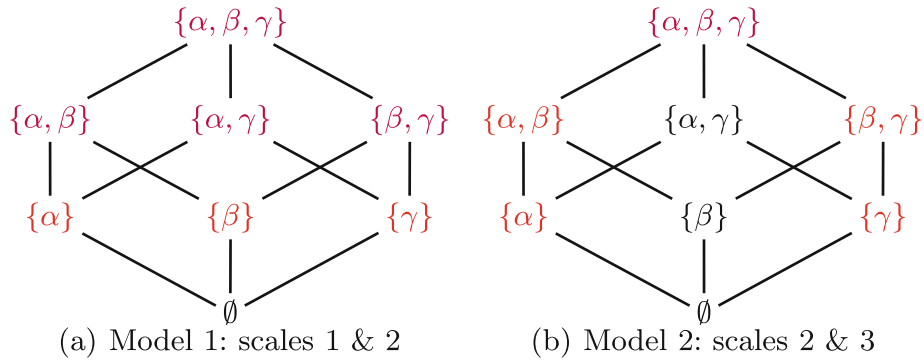
(a) Model 1: scales 1 & 2   (b) Model 2: scales 2 & 3

Fig. 2. Topological modelling of the classes of brain tissues, at the coarse/intermediate (a) and intermediate/fine scales (b). The labels coloured in red and purple are those for which the topology has to be preserved. The red labels need to be explicitly handled; the topology of the purple labels is preserved as a corollary of the topological preservation of the red ones. The topology of the black labels is authorized to evolve during the transformation process. (Color figure online)

4.1   Grid Refinement

We work on a space Ω defined as a subset of $\mathbb{Z}^3$. In order to carry out the deformation process at each scale, the space Ω has to be adapted to the current scale. It is important to note that the notion of simple points and homotopy-type are compliant with respect to digital grid refinement. In other words, a digital object X defined in $\mathbb{Z}^3$ (and more generally in $\mathbb{Z}^n$) has the same homotopy-type as its up-sampled analogue X_2 in $\mathbb{Z}^3$, defined by $x \in X_2 \subset \mathbb{Z}^3 \Leftrightarrow \lfloor x/2 \rfloor \in X$. In addition, x is a simple point for X iff there exists a sequence of successively simple points for X_2 composed from the 8 points of $2x + \{0, 1\}^3$. This topology-preserving octree refinement [1] remains trivially valid for up-samplings at any other (discrete) resolution.

In particular, we consider a scale factor $k \in \mathbb{N}$, $k > 1$, between the grids of each scale. The set $\Gamma_1 \subset \mathbb{Z}^3$ is the grid considered at the coarse scale S_1. It is refined, at scale S_2 into a second grid Γ_2 such that $\Gamma_1 = k\Gamma_2$, which means that one point of Γ_1 corresponds to k^3 points of Γ_2. Finally, Γ_2 is refined into a third grid Γ_3 such that $\Gamma_2 = k\Gamma_3$; this means that one point of Γ_1 corresponds to k^3 points of Γ_2 and k^6 points of Γ_3. Note that we have $\Omega = \Gamma_3$. It is then convenient to assume (without loss of generality) that Ω is defined as a Cartesian product $\prod_{i=1}^{3} [\![0, N_i - 1]\!] \subset \mathbb{Z}^3$ such that N_i is a multiple of k^2 for any $i = 1, 2, 3$.

4.2   Metrics

In order to guide the topology-controlled transformation process, we need to define metrics for assessing the error between the current (evolving) segmentation map and the target segmentation map. In particular, by minimizing a cost function associated to this error, our purpose is to make our segmentation map progressively converge onto the target, whereas correctly handling the topology.

In this context, we consider two metrics. The first is a classification metric, noted M_d, defined by the classification error at each point of the image. The second, noted M_Δ, is a distance-based metric, defined by the L_1 distance between the misclassified points and the corresponding, correctly classified region in the target image.

In order to build these two metrics, we first need to define fuzzy classification maps F_i from F (see Eq. (1)) at each scale i ($i = 1, 2, 3$). This is done with a standard mean policy:

$$F_i(x) = \frac{1}{k^{3.(3-i)}} \sum_{a=0}^{k^{(3-i)}-1} \sum_{b=0}^{k^{(3-i)}-1} \sum_{c=0}^{k^{(3-i)}-1} F(k^{(3-i)}x + (a, b, c)). \qquad (3)$$

In particular, we have $F_3 = F$.

For a given (crisp) segmentation map C, the first metric M_d assessing the error between C and F_i is then defined as:

$$M_d(C, F_i) = \sum_x \|C(x) - F_i(x)\|_2. \qquad (4)$$

For defining the second metric M_Δ, we build crisp classification maps G_i from the fuzzy maps F_i by a standard majority voting process, i.e. for any x, we set $G_i(x) = \arg_{\{\alpha, \beta, \gamma\}} \max F_i(x)$.

For a given (crisp) map C, the second metric M_Δ assessing the error between C and G_i is then defined as:

$$M_\Delta(C, G_i) = \sum_x \Delta(x, G_i^{-1}(C(x))) \qquad (5)$$

where $\Delta(x, X) = \min_{y \in X} \|x - y\|_1$ is the L_1 distance between the point x and the set X, whereas $G_i^{-1}(v) = \{x \mid G_i(x) = v\}$. In particular, we have $\Delta(x, G_i^{-1}(C(x))) = 0$ iff $C(x) = G_i(x)$.

4.3   Initialization and Optimization Process

The process is iterative, and proceeds from the coarse scale S_1 up to the fine scale S_3. For each step, the current input segmentation map is the output of the previous step (possibly up-sampled, if we switch between S_i and S_{i+1}). The only explicit initialization is then required for the very first step of the process. At this stage, we simply consider a three-layer nested sphere model, with a central simply connected full sphere of label α surrounded by a first hollow sphere of label β and finally a second hollow sphere of label γ.

At each step of the optimization process, we consider either the metric M_d or M_Δ. In order to make M_d decrease, we build a map that defines, for each point x and each possible relabelling $\ell_1 \to \ell_2$ (with ℓ_1 the current label at x), the associated benefit with respect to M_d, namely $\|\ell_2 - F_i(x)\|_2 - \|\ell_1 - F_i(x)\|_2$. Then, we iteratively carry out the relabelling of (simple) points with the maximal (non-negative) benefit, until stability.
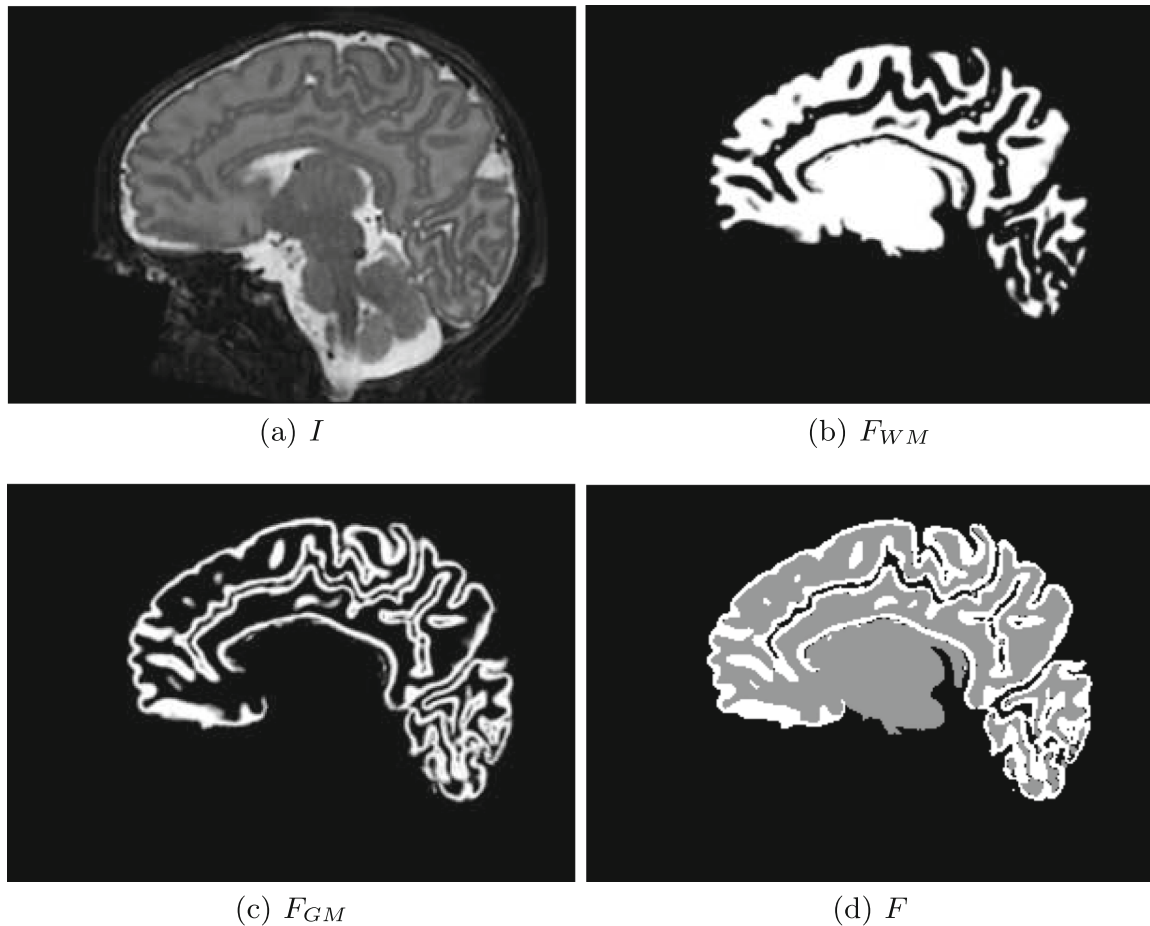
(a) I

(b) F_{WM}

(c) F_{GM}

(d) F

Fig. 3. (a) MR image. (b) Fuzzy classification of the WM from (a). (c) Fuzzy classification of the GM from (a). (d) Crisp classification map obtained from the fuzzy classification maps of (a) (WM in grey; GM in white; CSF + background in black). (a–d) Sagittal slices.

In order to make M_Δ decrease, we build a map that defines, for each point x and each possible relabelling $\ell_1 \rightarrow \ell_2$ (with ℓ_1 the current label at x), the associated benefit with respect to M_Δ, as $\Delta(x, G_i^{-1}(\ell_2))$ if $\Delta(x, G_i^{-1}(\ell_2)) < \Delta(x, G_i^{-1}(\ell_1))$ and 0 otherwise. Then, we iteratively carry out the relabelling of (simple) points with the maximal benefit, until stability.

5   Experiments and Results

We present some results computed with the proposed method, for topological correction of fuzzy segmentation maps obtained from the method proposed in [24] (or equivalent methods). An example of such map F obtained from an MR image is illustrated in Fig. 3.

Here, we carried out a 5 step iterative procedure with the meta-parameters summarized in Table 1.

The initial images I are defined on $\Omega = [\![0, 291]\!] \times [\![0, 291]\!] \times [\![0, 203]\!]$. We use as scale factor $k = 2$. The successive segmentation maps (and the associated

Table 1. Meta-parameters for the successive steps of the process.

Step	Scale	Topology	Metric
1	S_1	Model 1	M_Δ
2	S_2	Model 1	M_Δ
3	S_2	Model 1	M_d
4	S_2	Model 2	M_Δ
5	S_3	Model 2	M_Δ

(a) Step 1   (b) Step 2

(c) Step 3   (d) Step 4

(e) Result T (f) F
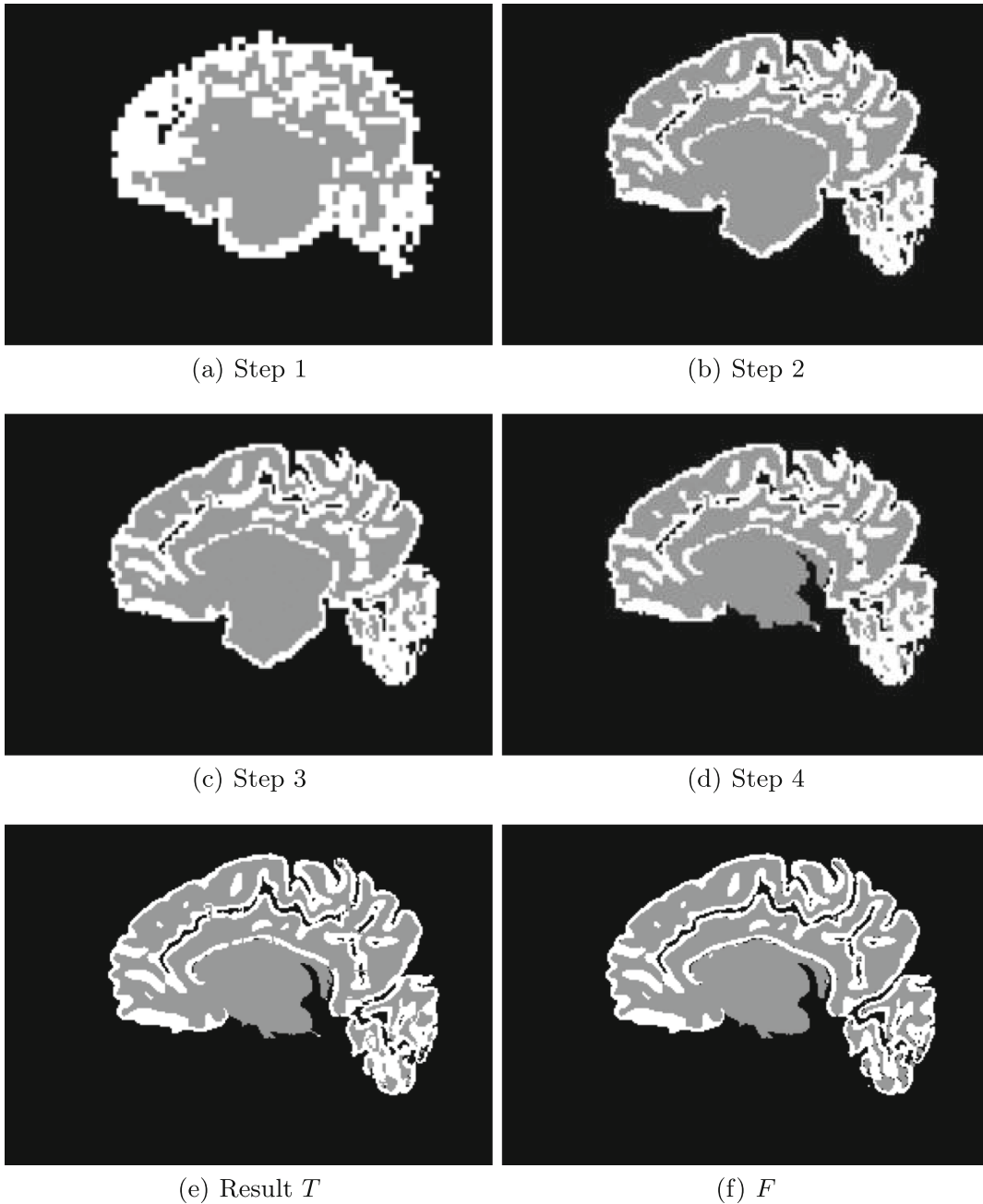
Fig. 4. (a–d) Intermediate results obtained by the successive steps of the process (see Table 1). (e) Final segmentation map. (f) Crisp classification map (see also Fig. 3(d)) used as reference for guiding the process.
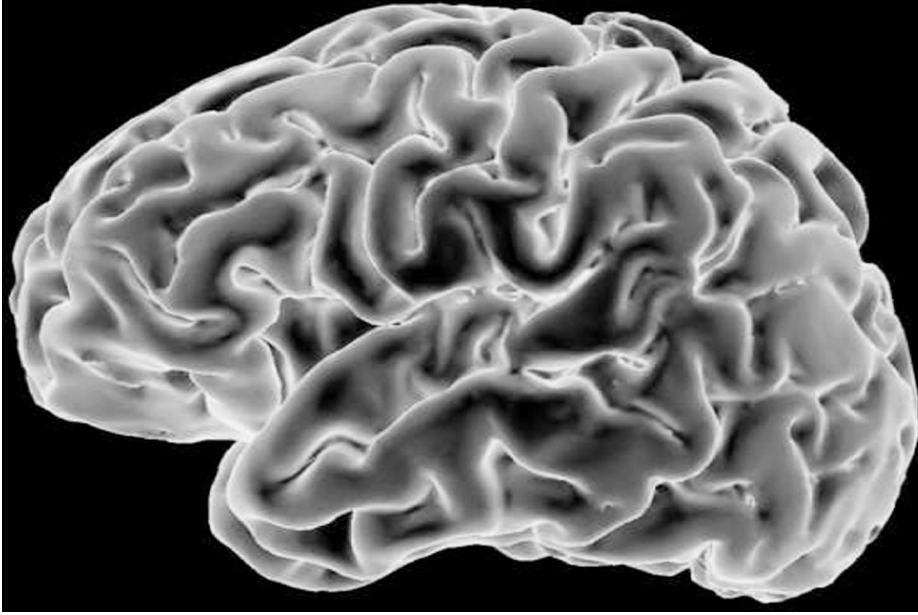
Fig. 5. Surface mesh generated from the final topological segmentation map T of Fig. 4(e).

classification maps F_3, F_2 and F_1) are then defined on $\Gamma_3 = [\![0, 291]\!] \times [\![0, 291]\!] \times [\![0, 203]\!]$, $\Gamma_2 = [\![0, 145]\!] \times [\![0, 145]\!] \times [\![0, 101]\!]$, and $\Gamma_1 = [\![0, 72]\!] \times [\![0, 72]\!] \times [\![0, 50]\!]$, respectively, i.e. with $|\Gamma_3| \simeq 1, 7.10^7$, $|\Gamma_2| \simeq 2, 2.10^6$ and $|\Gamma_1| \simeq 2, 7.10^5$.

An example of the successive steps of the topological transformation process is illustrated in Fig. 4. One can observe the progressive convergence of the model toward the classification map, whereas controlling the topology of the segmentation, in particular on the cortex (preserved on the upper part of the encephalus), whereas the GM is relevantly removed on the lower part, in accordance with the initial classification map and with the topological model.

A 3D mesh visualization of the resulting map T is illustrated in Fig. 5, qualitatively emphasizing the topological correctness of the result.

6   Conclusion

This preliminary study provides a proof of concept for the relevance of using the multilabel topological framework proposed in [16] for developing a multiscale, topological modelling of the cerebral structures, allowing one to either preserve or relax topological constraints over the power lattice of a set of elementary semantic labels.

In particular, this framework can be efficiently used for carrying out multiscale, topology-controlled deformation of label maps based on the concept of simple points, here in the context of topological correction of fuzzy segmentation maps computed beforehand.

Among numerous perspective works, we will further investigate (1) more sophisticated metrics for guiding the deformation process; (2) the possibility to

carry out deformation processes at a superpixel resolution and/or to use cubical complex models [18] for topological modelling; and (3) a richer modelling of the brain with more anatomical structures, e.g. for atlas-based segmentation.

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