Topology-preserving discrete deformable model: Application to multi-segmentation of brain MRI

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Context

3-D medical imaging (MRI, CT, ...) used for:

- pathology detection;
- quantification of pathological structures;
- surgery planning; etc.

Such data are:

- very large ($> 10^6$ voxels);
- semantically complex (several anatomical structures);
- numerous ($\Rightarrow$ few time for analysis).

$\Rightarrow$ (Semi-)automated segmentation of precious use for medical experts.

Motivation

Cerebral imaging: importance to provide "anatomically correct" segmentation results, *i.e.* with:

- a correct morphology ("shape");
- a correct geometry (size, volume, thickness, etc.);
- a correct topology (relations, connectedness, etc.).

Brain structures (visualised in MRI) are challenging, because of their anatomical complexity.

The issues of morphology and geometry are often considered: it is generally not the case of topology...

A (very) short state of the art

Very few segmentation methods devoted to 3D medical image segmentation with topological constraints.

Generally focused on "mono"-segmentation: vascular tree, cortex.

The problem of "multi"-segmentation has been considered recently:

- sequential approaches (Mangin 1995, Dokládal 2003);
- parallel approaches (Poupon 1998, Bazin 2007).

However, the problem of "correct" multi-segmentation actually remains an open problem (theoretical deadlocks, convergence issues, discrete space modelling, etc.)

Proposed method

Devoted to cerebral structure segmentation from T1 MRI.

It divides the intracranial volume into 4 classes:

- grey matter (GM);
- white matter (WM);
- sulcal cerebrospinal fluid (SCSF);
- ventricular cerebrospinal fluid (VCSF).

Properties:

- digital (inputs/outputs $\subset \mathbb{Z}^3$);
- parallel process ("volumic deformable model");
- non-monotonic;
- based on a *correct* topological framework (modulo "anatomical simplifications").

Simple points / simple-equivalence

Simple points (Bertrand 1994): enable to modify a binary object in $\mathbb{Z}^3$ without altering its topology: If $x \in X$ is (26- or 6-) simple for X, then $X \setminus \{x\}$ is homotopically equivalent to X.

Based on simple points, simple-equivalence also preserves homotopy type.

Definition (Simple-equivalence)

Let $X, X' \subset \mathbb{Z}^n$ ($n \in \mathbb{N}^*$). We say that X and X' are *simple-equivalent* if there exists a sequence of sets $\langle X_i \rangle_{i=0}^{t}$ ($t \geq 0$) such that $X_0 = X$, $X_t = X'$, and for any $i \in [1, t]$, we have either: (i) $X_i = X_{i-1} \setminus \{x_i\}$, where $x_i \in X_{i-1}$ is a simple point for X_{i-1}; or (ii) $X_{i-1} = X_i \setminus \{x_i\}$, where $x_i \in X_i$ is a simple point for X_i.

Brain anatomical hypotheses

Simple points and simple-equivalence: defined for binary objects. Multi-segmentation requires label image handling!

3 solutions:

- develop a sound topological framework for label images: no yet available (WIP...)
- use an incorrect (Poupon 1998) or simplified (Bazin 2008) topological framework for label images : not so good...
- propose simplified anatomical hypotheses enabling to handle label images as binary ones (done here).

Hypothesis: brain composed of 4 "tissue layers" hierarchically surrounded by each others: VCSF, WM, GM, SCSF (approximation of the reality at the considered resolution and w.r.t. T1 signal).

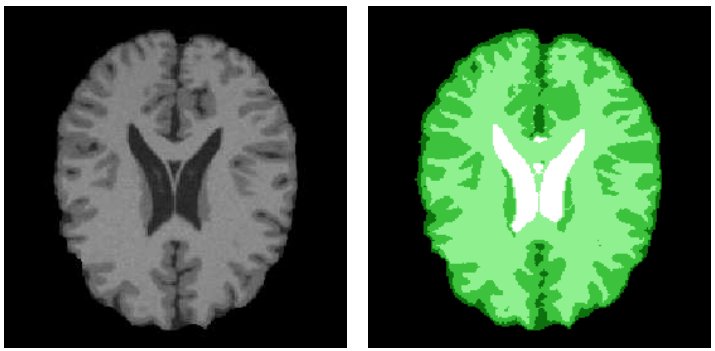
Input/output

Input:

- T1 MRI of the brain $I : E \rightarrow \mathbb{N}$, from which the intracranial volume $E' \subset E \subset \mathbb{Z}^3$ has been extracted;
- 2 threshold values $\mu_1 < \mu_2 \in \mathbb{N}$ delimiting the T1 signal intensity between CSF/GM, and GM/WM.

Output:

- partition $C = \{C_s, C_g, C_w, C_v\}$ of E', where C_s, C_g, C_w, and C_v correspond to SCSF, GM, WM, and VCSF classes.

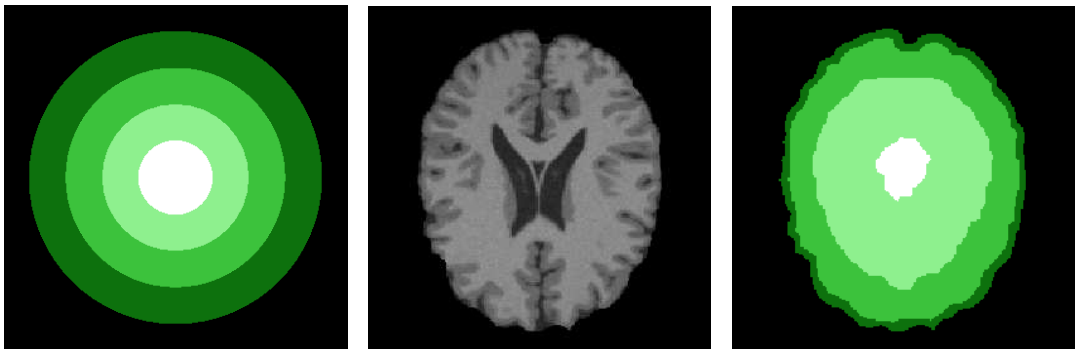


Initialisation

- Initial topological model C^i of E':
  - C_v^i: simply connected; successively surrounded by
  - C_w^i, C_g^i, C_s^i: topological hollow spheres.
- Use of a distance map computed from E', and dual adjacencies for the successive components

Remark

Topologically, C^i can be seen as a binary image made of $X = C_s^i \cup C_w^i$ and $\overline{X} = C_g^i \cup C_v^i$, in a $(26, 6)$-adjacency framework.



Discrete deformable model

Discrete deformable model: "deforming" the four classes without altering their topology until convergence.

- The model has to be topologically correct (initialisation).
- The process must preserve topology (simple-equivalence).
- The process has to be guided.

Remark

Modify the frontiers between the classes $\Leftrightarrow$ modify the frontier between the sets X and $\overline{X}$.

Remark

A simple point of X (or $\overline{X}$) is adjacent to exactly one connected component of X and one connected component of $\overline{X}$. Then (1) it is located at the frontier between two classes, and (2) there is no ambiguity regarding its reclassification.

Discrete deformable model

Deformation is guided by photometric constraints.

Cost provided for each point $x \in E'$: if $I(x)$ is not coherent w.r.t. the expected value interval (provided by μ_1, μ_2) of the class it belongs to, the distance between $I(x)$ and this interval is assigned as cost for x.

The deformation model iteratively switches "misclassified" simple points from one class to another, giving the highest priority to the "most misclassified" ones, until no simple point or no misclassified point is detected.

Algorithm

repeat

1 - *Frontier point determination*

$FP_{\{s,g\}} = (C_s^i \cap N_6^*(C_g^i)) \cup (C_g^i \cap N_{26}^*(C_s^i))$

$FP_{\{g,w\}} = (C_g^i \cap N_{26}^*(C_w^i)) \cup (C_w^i \cap N_6^*(C_g^i))$

$FP_{\{w,v\}} = (C_w^i \cap N_6^*(C_v^i)) \cup (C_v^i \cap N_{26}^*(C_w^i))$

2 - *Simple point determination*

$SP_{26} = \{x \in X \mid x \text{ is 26-simple for } X\}$

$SP_6 = \{x \in \overline{X} \mid x \text{ is 6-simple for } \overline{X}\}$

3 - *Candidate point determination*

$CP = (SP_6 \cup SP_{26}) \cap (FP_{\{s,g\}} \cup FP_{\{g,w\}} \cup FP_{\{w,v\}})$

4 - *Cost evaluation*

for all $x \in CP \cap FP_{\{s,g\}}$ (resp. $CP \cap FP_{\{g,w\}}$, resp. $CP \cap FP_{\{w,v\}}$) **do**

$v(x) = I(x) - \mu_1$ (resp. $I(x) - \mu_2$, resp. $I(x) - \mu_1$)

if $x \in C_g^i$ (resp. C_w^i, resp. C_w^i) **then**

$v(x) = -v(x)$

end if

end for

5 - *Point selection and reclassification*

if $\max(v(CP)) > 0$ /* with $\max(v(\emptyset)) = -\infty$ */ **then**

Let $y \in CP$ such that $v(y) = \max(v(CP))$

Let $C_\alpha^i \in \{C_s^i, C_g^i, C_w^i, C_v^i\}$ such that $y \in C_\alpha^i$

Let $C_\beta^i \in \{C_s^i, C_g^i, C_w^i, C_v^i\}$ such that $y \in FP_{\{\alpha,\beta\}}$

$C_\alpha^i = C_\alpha^i \setminus \{y\}$

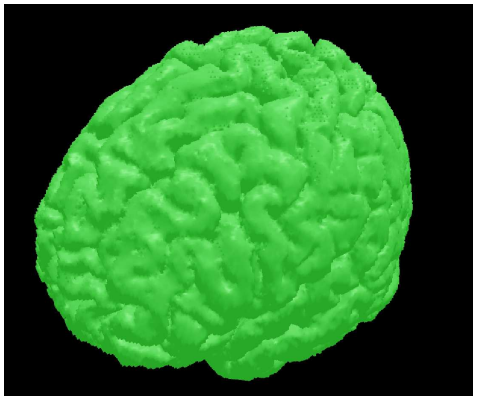
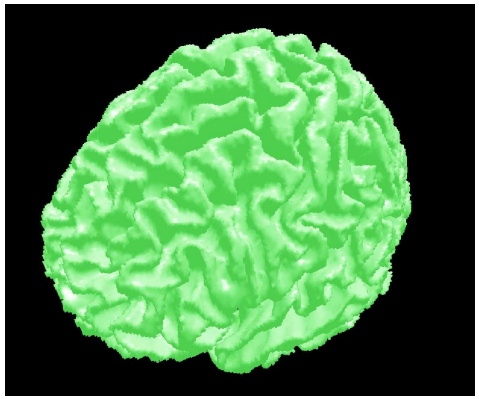
$C_\beta^i = C_\beta^i \cup \{y\}$

end if

until $\max(v(CP) \leq 0)$

Results

- Optimal algorithm (FIFO lists): linear complexity $O(|E'|)$.
- Computation time approx. 1 to 2 minutes (non-optimised implementation, 256^3 data).


Validations

- Ground truth: BrainWeb data.
- Compared to a "statistically-based" method (Bricq 2006).
- Quantitative criteria: sensitivity ($tp/(tp+fn)$), specificity ($tn/(tn+fp)$) and similarity ($2.tp/(2.tp+fp+fn)$).
- Qualitative criteria: topology preservation.

Quantitative point of view: good for "clean" data, but not perfect for other ones (noise, signal distortion vs. photometric constraints).

Qualitative point of view: good w.r.t. chosen hypotheses (ex.: cortex = thick surface; ventricles surrounded by GM, etc.).

Contribution and further works

Preliminary work related to the parallel discrete topology-preserving segmentation of structures from 3D medical data.
Encouraging results (non-monotony, convergence, topological correctness, etc.), but:

- anatomical simplified hypotheses;
- non-sophisticated guidance of the model.

Further works:

- develop a sound theory for label image topology handling $\longrightarrow$ anatomically correct hypotheses;
- develop "sophisticated" guidance constraints without significantly altering complexity, and preserving convergence.

Two challenging issues!

Thank you for your attention

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