DEFORMABLE TOPOLOGICAL MODELS FOR SEGMENTATION OF 3D MEDICAL IMAGES

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Abstract–We propose to make low level segmentation of 3D medical images rely on deformable topological models. An initial label image made up of a set of deformable regions is endowed with a priori known topological properties of the desired result. Then, multi-scale topology preserving deformations are applied to this image in order to minimize a global energy whose form stems from the Gibbs Random Field domain. This new segmentation framework leads to important improvements of previous works. First, topological regularization is included in the segmentation process which results in better robustness of posterior processing like skeletonization. Second, the topological arrangement allows discrimination between objects of similar intensities. Third, interface between two deformable regions behaves like a deformable surface but surface regularization relies on Ising model rather than on differential terms. This results in a better behaviour with highly convoluted objects like the cortex. Finally, this approach allows the management of interactions between several deformable objects.

1. INTRODUCTION

Embedding of a priori knowledge in "low level" image processing appears often necessary for increasing robustness of "high level" post-processing. In fact, the development of model based treatments turns out to be easier in the field of 3D medical images than in other fields like computer vision or satellite image processing. Indeed, since apart from potential pathologies the underlying anatomical models are fixed, the development of generic algorithms dealing with any pattern of a database or any geographic map is not required. Moreover, volumetric images provide a dense 3D description of the whole object rather than several 2D views involving complex stereovision problems. Lastly, the voxel intensity value is generally related in a simpler way to the underlying physical property than when complex illumination models have to be taken into account. In this paper, we propose a new framework for the management of model-based low level processing. This framework intends to provide ways of designing high level pattern recognition systems driving low level segmentation according to their need.

During last decade, models stemming from Physics like deformable surfaces [3] or Gibbs Random Fields (GRF) [4] have gained increasing popularity in the field of image processing. This success calls for the development of methods combining the leading points of both approaches. Recent works in 3D discrete topology have given rise to efficient tools to construct topology preserving deformations [5]. Hence, the idea of dealing with deformable regions rather than deformable surfaces can be addressed practically, which provides a way of performing such a combination. We propose to make low level segmentation rely on a model made up of deformable regions initially endowed with a priori known topological properties. This model is simply a label image, each label defining a region. Then, segmentation amounts to applying topology preserving deformations in order to reach an energetic goal, or more generally a sequence of energetic subgoals designed from a higher level of processing.

This framework can be viewed as a flexible alternative to the well-known elastic matching paradigm [1]. Indeed, we think that elastic matching is doomed to fail in regions of high anatomical variability because of problems of initialization, over-regularization (elasticity constraints), and ill-adaptation to structural variability. In return, our framework can include a wide variety of a priori knowledge and could be driven by higher levels of processing in charge of parameter adaptation and of creation or deletion of additional templates (which could allow the management of pathologies). In our opinion, this framework could be used for giving to models stemming from artificial intelligence the possibility to backtrack until the low level processing stage.

2. DEFORMABLE TOPOLOGICAL MODELS

2.1. Energy defining the segmentation goal

Surface regularization is naturally embedded in our framework using GRF forms of energy, which allows greater flexibility than Tikhonov forms of regularization [9] as regard convoluted objects like the cortex. Thus, the energy E_g whose global minimum corresponds to the goal of the segmentation has the form of a clique potential sum classically composed by two terms: a data driven term which is a simple model of intensity processes and a regularization term expressed via Ising or Potts models [4] (the Potts model is simply the extension to n classes of Ising model).

$$E_g = \sum_{C_M} V^a_{l(M)}(i(M)) + \sum_{C_{M_1M_2}} V^P(l(M_1), l(M_2)) \ , \tag{1}$$

where $l(M)$ is the current label of point M, $i(M)$ is the intensity of M in the data image, C_M is the order 1 clique attached to M and $C_{M_1M_2}$ is the order 2 clique attached to 6-neighbours M_1, M_2. V_l^a are basin-shaped functions roughly modeling for each region statistical knowledge on intensities and V^P is a matrix of adjacency costs related to Potts model (see Fig.4). Analogy with deformable contour approaches is straightforward. The interface between two deformable regions behaves like a deformable surface regularized by Ising model rather than by a differential term. Data contribution to the global energy does not rely on potentials attracting the deformable surface towards edge points previously extracted by an edge detector [3] but on intensity-based potentials acting on both delimited regions. In this way, one interface can be selected among several ones using differences between object intensities or textures.

2.2. Topological constraints

Topological constraints are imposed region by region. The topology of a given region is defined relatively to the background made up by the union of all other regions. Connectivity choice may appear as a problem because of the well-known difficulties related to Jordan theorem. Indeed, since we are potentially dealing with more than two regions, the classical choice of different connectivities for object and background seems no more possible (considering for this choice 6-connectivity and 26-connectivity as the only available possibilities). In fact, since one region is always considered relatively to the union of the others, this classical solution remains possible: whatever the connectivity chosen for a given region, the dual connectivity has to be used for its background. Nevertheless, further investigations should be done on this subject in order to check that this cannot results in deadlocks for topology preserving deformations. For the application involving more than two regions presented in this paper, such difficulties have been avoid thanks to a particular property of the topological model used to represent the head. Since this model is made up of nested regions (see Fig.3), 6-connectivity and 26-connectivity have been alternatively chosen from the outer most region until the inner most one. Hence, each interface separates two regions endowed with dual connectivities. Three types of topological constraints can be imposed during deformations:

1. **Homotopy preservation:** the region is subject to homotopic deformations which preserve region connected components, cavities and "tunnels" (see [6] for a precise definition of homotopy relying on the notion of digital fundamental groups). Homotopic deformations are constructed as sequences of simple point additions or deletions. Simple points are efficiently characterized by the computation

of two local connected component numbers [5]. Intuitively, simple points are points whose neighbourhood contains exactly one connected component of object and background. Multi-scale homotopic deformations can be constructed thanks to the link between discrete topology and topology of the underlying continuous objects. This allows reduction of computation time and better robustness to noise.

2. **Connectivity preservation:** this weaker constraint is imposed in a similar way by sequential addition of object adjacent points or deletion of points whose neighbourhood contains exactly one connected component of the object. Thus cavities or "tunnels" can be created or deleted but the object can not split in several connected components. This constraint is used for object of complex topology like cerebro-spinal fluid (CSF) or skull.

3. **Adjacency interdiction:** this constraint is naturally embedded in interface regularization potentials through a simple modification of Potts model [8]. Prohibited adjacencies correspond to infinite values of the function V^P attached to order two cliques (see Fig.4).

It should be noted that these three types of constraints are far to be independent. Furthermore, they are often redundant. For instance, when a region A is surrounded by a region B whose homotopy is preserved, if the only authorized adjacency for A is with B, then A homotopy will be preserved too. Therefore, since computation cost of homotopy preservation is high, a judicious choice of the topological constraint set is important.

3. ENERGY MINIMIZATION

3.1. Energy non-convexity

Energy minimization based methods usually suffer from one major impediment: the non-convexity of the function to be minimized. Apart from mainly heuristic solutions, two general approaches are used to overcome this difficulty: either providing a good initialization to a fast deterministic algorithm yielding the nearest local minimum or employing a stochastic algorithm. Simulated annealing has been a great success during last decade when dealing with functions involving a large number of parameters. Nevertheless, since practical implementations are only approximations of the theoretical SA, they do not perform well for any energetic landscape. A very favourable behaviour of SA has been proved in the context of GRF [4], which has led to important results in the image processing field. Unfortunately, this important property is no more verified in the context of deformable regions, which does not belong to the

GRF framework (label images which do not respect the topological properties imposed from the initial image would have a null probability which is incompatible with Gibbs distributions). Indeed, since the introduction of global topological constraints and of infinite potentials preventing some adjacencies forbids most of label image configurations, the number of possible paths between the initial image and the global minimum (or the local minimum of interest) is very reduced. Hence, when the initial image is too far from this global minimum, the paths to follow often contain high barriers which results in a bad behaviour of SA implementations. Such barriers are mainly induced by interferences between regions attracted by similar intensities. Indeed, a misplaced region overlapping the data domain aimed at a concurrent region often has to cross a domain of repulsive intensities before reaching the correct data domain. Owing to these difficulties, SA cannot be applied in the usual way in the context of deformable regions. Nevertheless, SA will turn out to be a powerful tool during the design of problem-dedicated minimization algorithms.

3.2. Problem-dedicated minimization algorithms

In favourable cases, a simple initialization is sufficient to obtain good results with deterministic algorithms like Iterated Conditional Modes (ICM) [2]. For more complex situations, problem-dedicated initialization algorithms have to be designed in order to feed ICM. Such an initialization algorithm has to position each interface in such a way that no interference between concurrent regions remains. A powerful way of designing such algorithms consists in the construction of a sequence of energetic intermediate goals corresponding to a sequence of locations in the configuration space which last element is the minimum of interest of E_g. Each energetic intermediate goal is constructed through modifications of the conventional energy E_g intending to flatten a barrier which prevents to reach the next location in the sequence. This approach shows strong analogies with a well-known toy where the player has to drive a marble between places of a plane maze by modifying the plane inclination relatively to the gravity field. Energy modifications are performed either through deletion of some potential families constituting E_g (see Fig.4) or through addition of new potentials introducing for instance global knowledge on object shapes (see Fig.5). These additional potentials tend to act like pressure forces used in active contour approaches [3]. The whole deformation process is performed via a multi-scale implementation. Therefore, the initialization process is restricted to the higher level of the scale pyramid. Thus the use of SA for each successive minimization is possible keeping reasonable computation times, which results in a greater robustness to local minima. SA is initialized at an intermediate temperature and thus is not able to cross high barriers which legitimates this sequence of successive SA initializations (SA is trapped in a restricted configuration area delimited by high barriers). After this initialization process, segmentation is refined by successive deterministic minimizations of E_g with increasing resolution (see Fig.1).

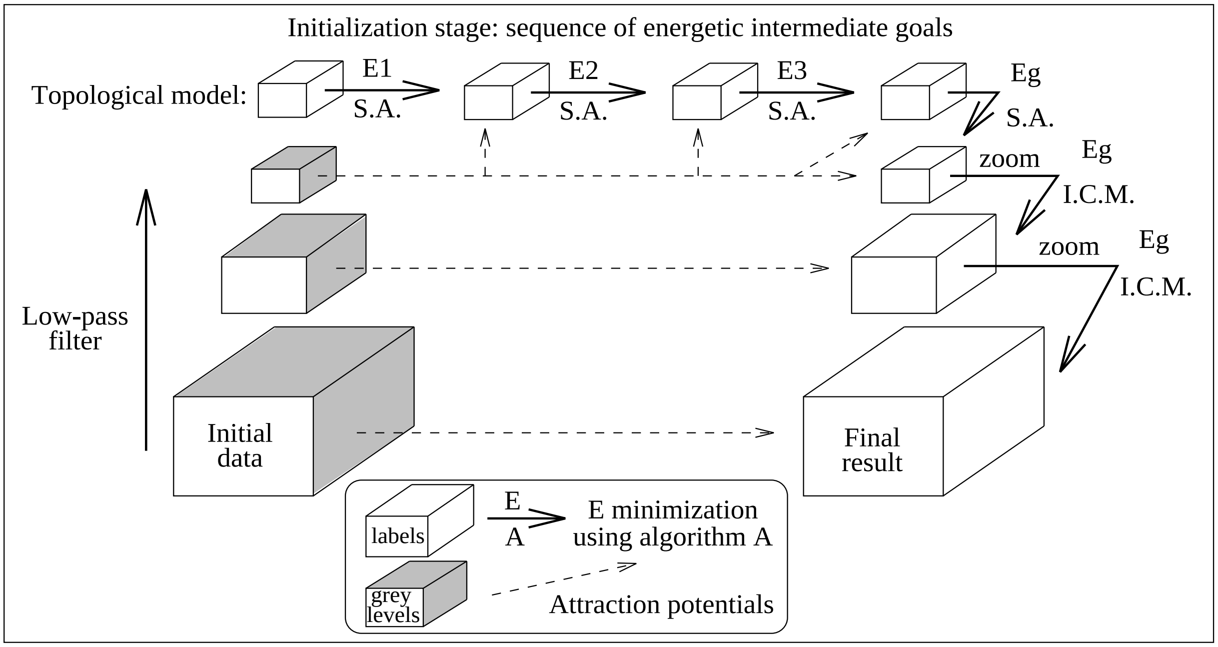


Figure 1: Multi-scale implementation of the segmentation process

4. PRACTICAL RESULTS

Two different applications of deformable topological models are proposed. The first one is an illustration of contributions of this approach in the preprocessing steps of a high level pattern recognition system. The second one, which uses a more complex model, describes the implementation of a dedicated minimization algorithm based on the principle described above.

4.1. Segmentation of the union {CSF, gray matter}

The deformable region principle has been included in a sequence of processes allowing the construction of a high level description of the cortex topography from a T1-weighted magnetic resonance (MR) image [6]. The aim of this work is the automatic identification of the main cortical folds. Successive steps of the method are the following:

1. Brain segmentation using 3D mathematical morphology.

2. Segmentation of the union of gray matter and CSF using a single homotopically deformable region (HDR) embedded in the background.

The initial region is the empty parallelepipedic bounding box of the brain. Hence the HDR is endowed with the homotopy of an empty sphere. Several multi-scale homotopic geodesic dilations allow a first deformation of the initial region in order to make it match the brain hull. Then homotopic deformations are applied in order to make the region internal surface reach the gray matter/ white matter interface (see Fig. 2). Parameters of attraction potentials are estimated from an initial rough classification using the K-means algorithm. Parameters measuring the relative influence of attraction potentials and regularization (Ising model) are chosen according to local considerations on the interface geometry [6]. Deterministic minimization is performed using an ICM-like algorithm.

3. Homotopic skeletonization of the previous region (see Fig. 2).
4. Segmentation of the skeleton in simple surfaces mainly corresponding to cortical folds [5].
5. Construction of an attributed relational graph whose nodes are these simple surfaces.

In this application, contribution of the deformable topological model approach can be considered from two point of views. First, compared with conventional deformable surface methods, it allows segmentation of a highly convoluted contour including surface regularization. Second, compared with conventional classification methods (like GRF), the result topology is imposed (with other approaches, post-processing could fill cavities but there is no simple way to detect "tunnels") which increases the robustness of the following skeletonization. The whole method described above, applied to fifteen brains, has turned out to be especially robust as regard various acquisition parameters. A graph database has been constituted from which a structural model of the cortical topography has been inferred [7]. We experiment today with the final goal, the automatic recognition of the cortical folds.

4.2. Tissue classification in MR images of the head

Segmentation of 3D T1-weighted MR images of the head has been performed with a simple model made up of nested regions, namely from the outer most to the inner most region: *void, skin, skull, CSF, gray matter, white matter and ventricles* (this last one made up of two connected components) (see Fig.3). Attraction potential parameters are estimated through a rough procedure relying on a sample of regions of interest (see Fig.4). Different topological constraints are imposed according to the

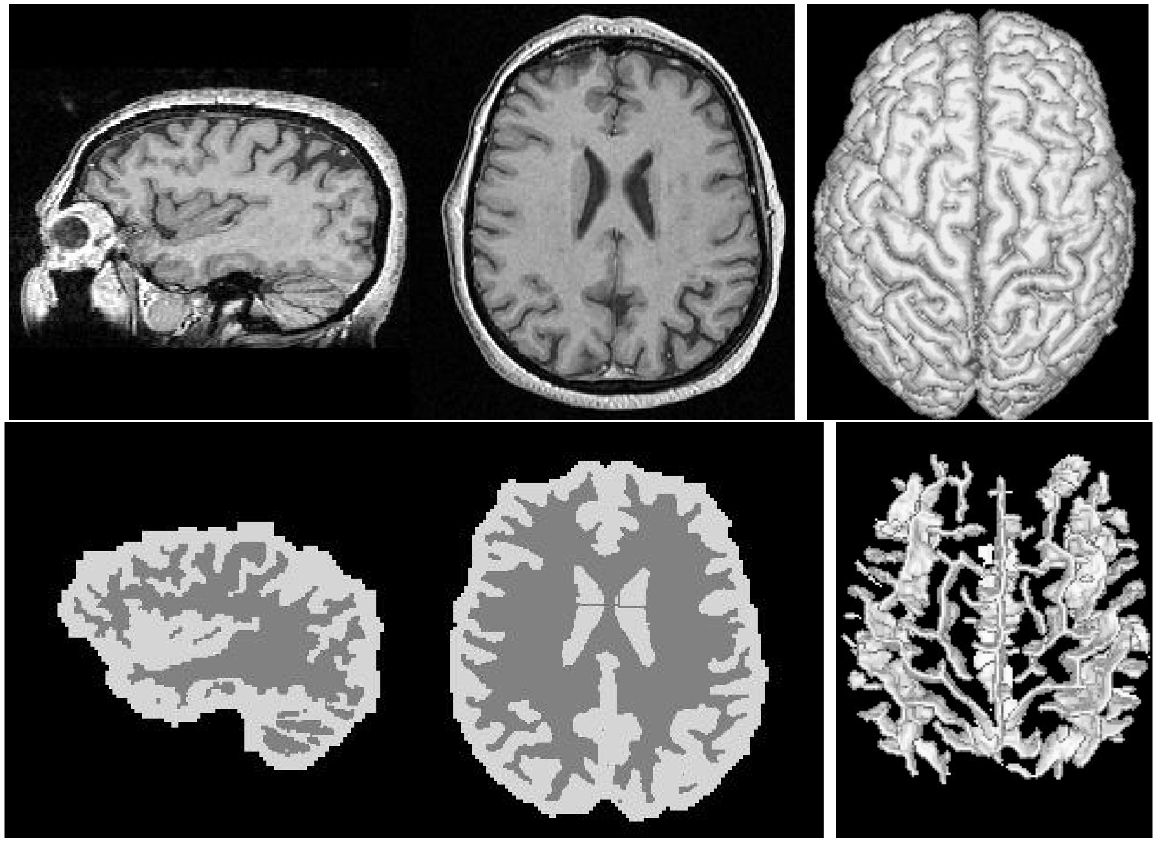


Figure 2: *Up left:* Two orthogonal slices of the T1-weighted MR image (124 axial slices 256×256 , pixel size: 1mm, slice thickness: 1.3mm, scanner: Signa GE); *Up right:* 3D rendering of the brain surface; *Down left:* Segmentation of the union {gray matter, CSF} using the HDR method (it should be noted that since we are only interested in the shape of the segmented object, the bad localization of the skull/CSF interface provided by morphological steps is not a problem); *Down right:* 3D rendering of a subpart of the segmented object skeleton.

topology of real objects (see Tab.1). The dedicated initialization process makes use of three types of pression-like additional potentials (see Fig.5). Three subgoals $E1, E2, E3$ are defined to drive three problematic region interfaces in respectively aimed areas (see Tab.1). A simple analogy with nested inflating or deflating balloons help to understand the process.

$E1$: Attraction potentials of *skin, skull and CSF* are superseded by low positive external fields and a negative external field is added to *void*. Thus *void* drives *skull* and *CSF* inside the head which allows a good positioning of the *void/skin* interface. It should be noted that keeping attractive potentials of *gray, white* and *ventricles* active prevents *skin* penetrating too deep inside the brain. This illustrates a leading guideline during energetic subgoal design: when flattening an obstructing barrier in order to reach a specific configuration area, other barriers delimiting this area have to be preserved.

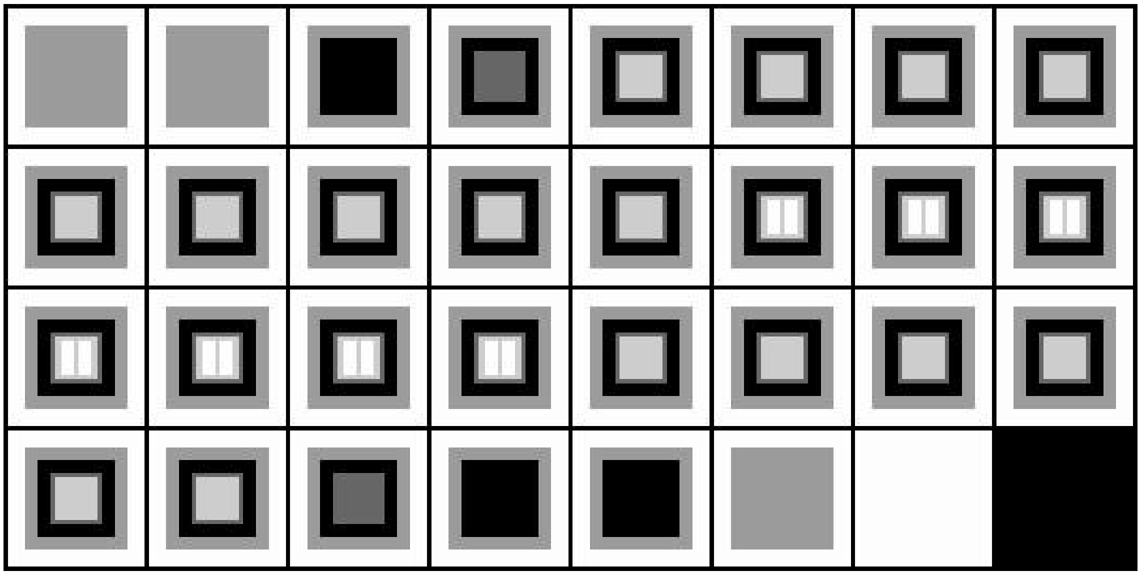


Figure 3: Topological model of the head made up of nested regions (void, skin, skull, CSF, gray and white matter, ventricles) apart from the lowest part modeling the neck.

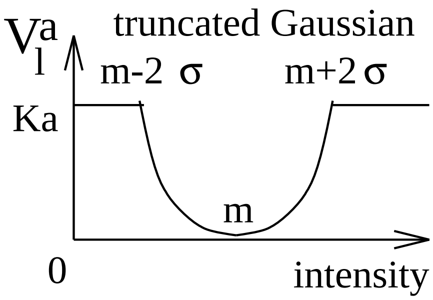
Table 1: Sequence of Energetic intermediate goals (H denotes homotopy preservation and C connectivity preservation)

		Order 1 cliques								Order 2 cliques				Shape global terms							
	Top.	Attraction				Ext. field				Potts				Volume				Surface			
	E	1	2	3	g	1	2	3	g	1	2	3	g	1	2	3	g	1	2	3	g
v	H	×	×	×	×	×	×			×	×	×	×								
s	H			×	×	×	×			×	×	×	×								
s	C			×	×	×	×			×	×	×	×								
C	C			×	×	×	×			×	×	×	×							×	
g	H	×	×	×	×					×	×	×	×			×				×	
w	H	×	×	×	×					×	×	×	×			×					
v	H	×	×	×	×					×	×	×	×			×					

$E2$: The second energy stems from a slight modification of $E1$ (increased external field for *skin*) intending to penalize *skin* in order to expel it from inside the brain. *Skin* is then reduced to a thin layer which results in the positioning of the *skin/skull* interface in the aimed area. Decoupling first and second steps allows greater robustness. Indeed, since barriers are flattened one by one, side effects of energy modifications are better controlled.

$E3$: The third energy relies on introduction of simple knowledge on the brain shape. A first global term acting on the number of points of the union {*gray, white, ventricles*} imposes a range of acceptable brain volumes, a second global term acting on the number of voxel faces belonging to the *CSF/gray* interface imposes a range of acceptable brain surfaces. Indeed, since the initialization process occurs at a low resolution level, brain folds do not contain CSF. Hence, this

Attraction potentials: basin-shaped functions V_l^a are attached to order 1 cliques.



An example of statistical parameters*

	v	s	s	C	g	w	v
m	2	80	10	40	85	110	40
σ	10	20	10	10	5	5	10

Modified Potts model: (regularization and adjacency interdiction) $V^P(l_1, l_2)$ is attached to order 2 cliques.

$$V_P = \begin{array}{c} \begin{array}{ccccccc} v & s & s & C & g & w & v \end{array} \\ \left(\begin{array}{ccccccc} 0 & K_r & \infty & \infty & \infty & \infty & \infty \\ K_r & 0 & K_r & \infty & \infty & \infty & \infty \\ \infty & K_r & 0 & K_r & \infty & \infty & \infty \\ \infty & \infty & K_r & 0 & K_r & \infty & \infty \\ \infty & \infty & \infty & K_r & 0 & K_r & \infty \\ \infty & \infty & \infty & \infty & K_r & 0 & K_r \\ \infty & \infty & \infty & \infty & \infty & K_r & 0 \end{array} \right) \end{array}$$

$\star$: the statistical parameters (means and standard deviations) are roughly estimated from regions of interest.

Figure 4: Potentials of the conventional energy

External field: this corresponds simply to non zero constant potentials attached to order one cliques for some labels (a positive constant favours this region expansion, while a negative one has the reverse effect). This kind of potentials is related to external magnetic fields in the GRF domain.

Volume information: global potentials of the form $K_v(n - N)$ intend to introduce volume information in the global energy, where n is the current number of points belonging to a union of regions, N is an ideal volume to be reached and K_v is a positive constant which balances this contribution.

Surface information: global potentials of the form $K_s(s - S)$ intend to introduce surface information in the global energy, where s is the current number of voxel faces belonging to a specific interface between two regions, S is an ideal surface to be reached and K_s is a positive constant which balances this contribution.

Figure 5: Toolbox of pression-like potentials for initialization

shape parameters are relatively stable between individuals and have been estimated from several previously segmented brains. This step intends to expel the brain from the skin area which results in a good positioning of the *CSF/gray* interface.

This initialization process is followed by a deterministic minimization of the conventional energy Eg from which all pression-like terms have been deleted.

In order to check the relevance of the method, the whole segmentation process has been applied first with a simulated image containing six convoluted areas whose respective intensities had same statistics than *void, skin, skull, CSF, gray* and *white matters* in a sample MR image. Moreover this simulated image was containing topogical incoherences relatively to the model (connections between gray matter and skull). The segmentation process has nicely retrieved the non-noisy image and has corrected these topological incoherences (see Fig.6). Then, the segmentation process has been applied to two different high resolution MR images with the same sequence of steps (the whole process takes about one hour on a SPARC station 20). In both cases, segmentation results appear especially good in the head part where the topogical model is relevant, namely slices located above eyes (see Fig.7). In the lowest part of the head, result quality decreases progressively with the apparition of large objects not taken into account in the model, which could be foreseeable.

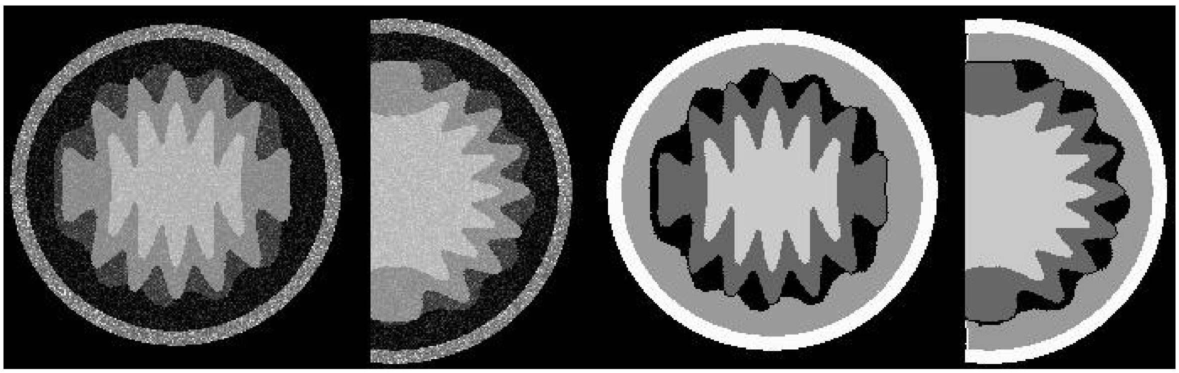


Figure 6: Segmentation result with the simulated image (left: two orthogonal slices of initial data, right: segmentation result)

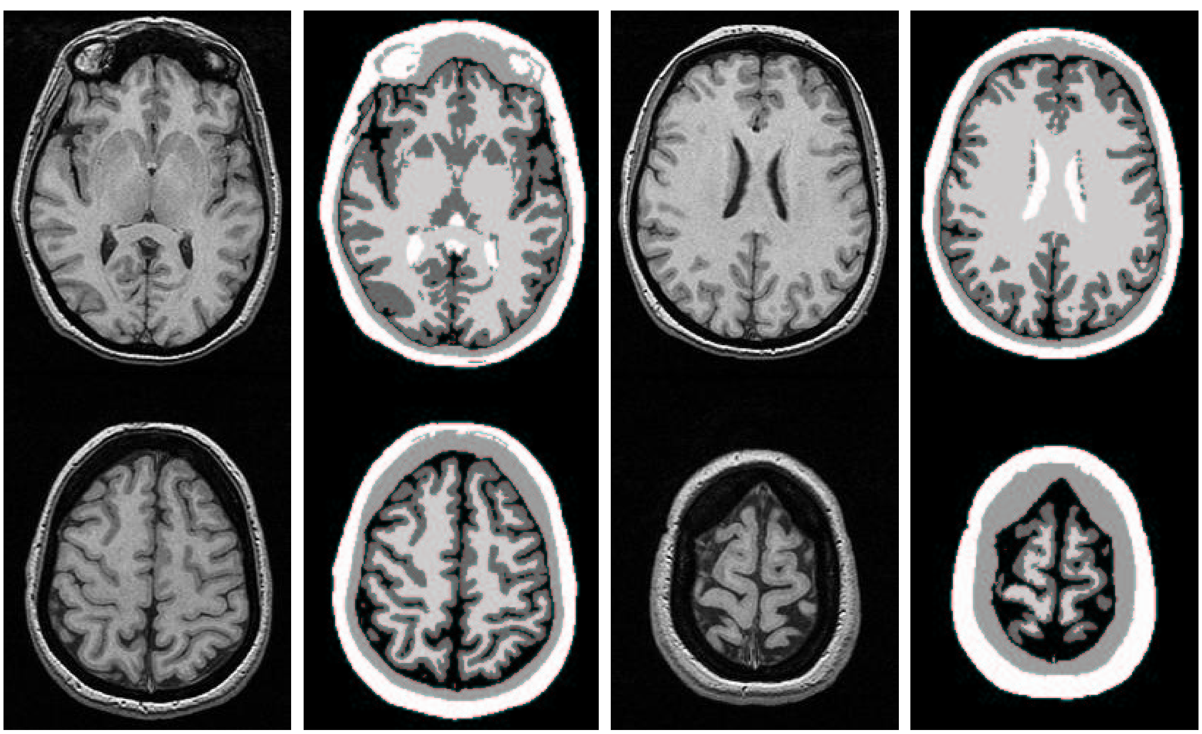


Figure 7: Segmentation result for a few slices located above the eyes

5. CONCLUSION

A new framework has been proposed in order to include topological regularization in a segmentation method dedicated to 3D medical images. This approach allows robust detection of convoluted interfaces, robust skeletonization and discrimination of tissues showing similar intensities, which has been illustrated by two different applications with 3D MR images. Further work intends to apply this framework to the segmentation of various nuclei embedded inside the brain. In order to overcome complex interferences with the lowest part of the head, this work will rely on a prior robust segmentation of the brain using 3D mathematical morphology. The toolbox of initialization dedicated potentials will be enriched in order to use other kinds of global knowledge (object location in a reference frame, distances between object centers of gravity, finer shape information...). The challenge will be to make a higher level system drive the initialization process, in order to make backtrack possible. Then problems induced by potential presence of local pathologies could be addressed.

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