Active Surface Models for Brain Imaging

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INTERDISCIPLINARY INVERSION WORKSHOP 5 - POSTER SESSION 9

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ABSTRACT

Given

- A 3D volume of data, e.g. medical images of the brain.

Objectives

- To solve the non-linear inversion problem of reconstructing the boundaries of (medical) objects in the data.

Method

- We shape a closed surface of triangles to the object.
- The fitting is carried out by means of minimising an energy function.

Usage

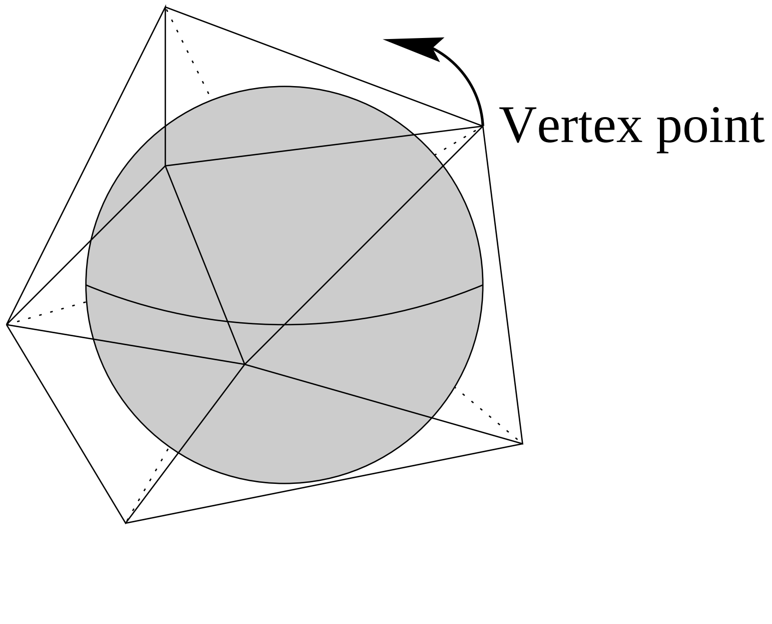
- The surface can be used to visualise the object and to make quantitative mesurement of the object.
- Applications are many, we show MR volumes.

SOLUTION STRATEGY

- The algorithm will require an initial surface (boundary estimate) of the object, represented as a mesh of triangles.
- The adaptation of the surface will be preformed as an energy minimisation task.

$$E_{\text{total}} = \sum_k \alpha_k E_k \quad ,$$

  The different energy terms represents different properties of the surface. They are weighted by α_k.
- The minimisation is carries out in an iterative fashion, adapting one vertex per iteration.



SYMBOLS

- i : The vertex number, i.e., number of the triangle corner.
- j : The triangle number.
- $N_i = \Sigma_i 1$: Number of triangles.
- $N_j = \Sigma_j 1$: Number of vertices.
- $V(\boldsymbol{x})$: The value of the volume at $\boldsymbol{x}$.
- t : iteration number.

THE ENERGY TERMS

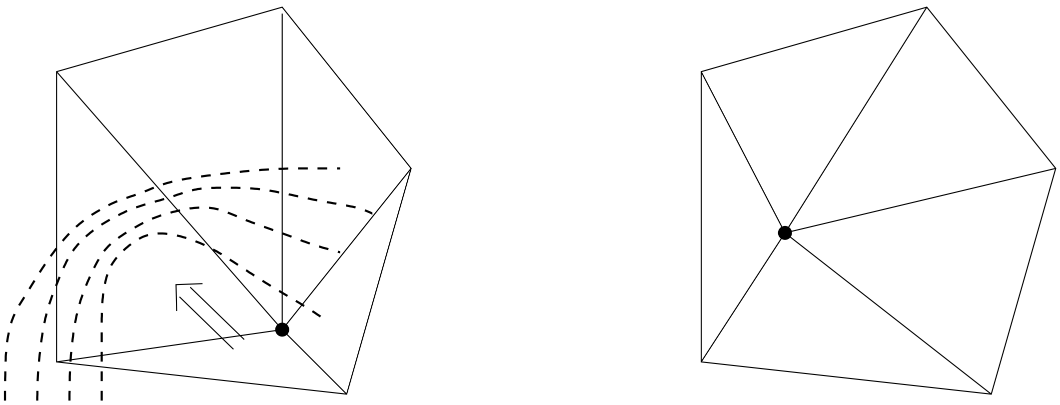
Here follows a list of various energy terms that we use.

The Potential

The surface must be adapted to the boundary of the object. A good starting point for the potential is the (-) squared magnitude of the gradient.

$$E_{\text{Potential}} = -\sum_i S_w |\nabla V(\boldsymbol{x}_i)|^2$$

where S_w is a spatial smoothing operator with a characteristic distance of w.



- The width w can be adapted during the optimization in order to fine tune the boundary estimate.

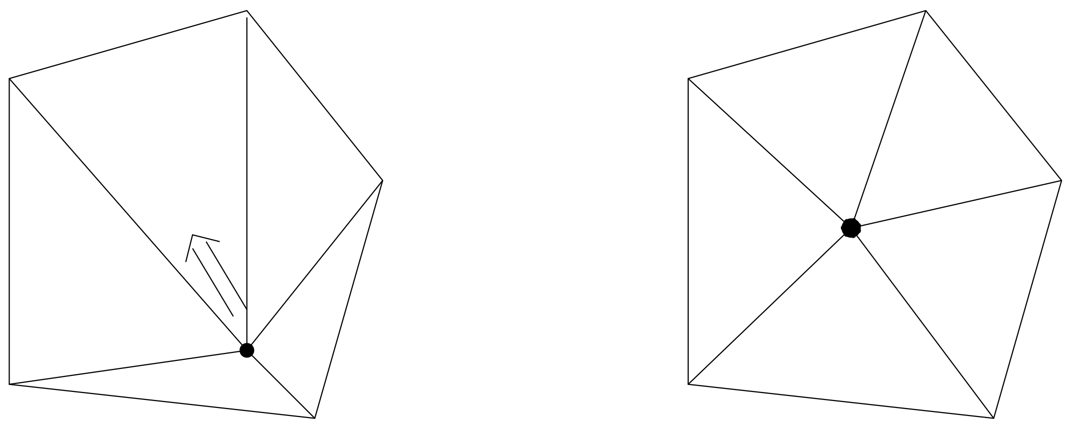
THE ENERGY TERMS

Smoothing

This term tries to minimise the squared distance to the center of mass of the vertex neighbours.

$$E_{\text{Smooth}} = \sum_i \left(\boldsymbol{x}_i - \boldsymbol{x}_{N(i)}\right)^2$$

where $\boldsymbol{x}_{N(i)}$ is the mean neighbours vertex position.



- This energy term will try to keep smoothness. Note it implies a shrinking effect, because the global minimum of this smoothing term is found where all vertex positions are equal.

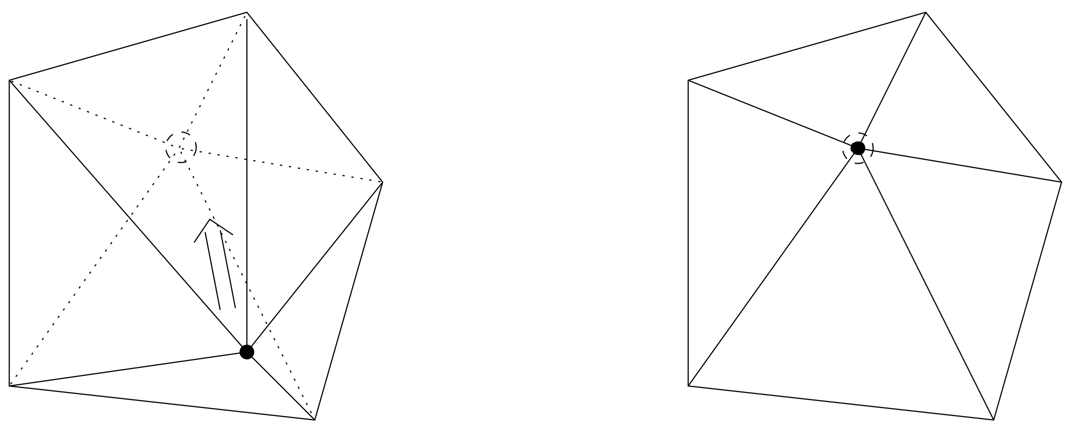
THE ENERGY TERMS

Inertia

One can add an "inertia" term that prevent large movements away from the initial vertex positions.

$$E_{\text{Inertia}} = \sum_i \left(\boldsymbol{x}_i - \boldsymbol{x}_{i,org}\right)^2$$

where $\boldsymbol{x}_i$ is the current position of vertex point i and $\boldsymbol{x}_{i,org}$ is the original position of the same vertex point.



- This term reflects the reliability of the initial surface.

THE ENERGY TERMS

Template Matching

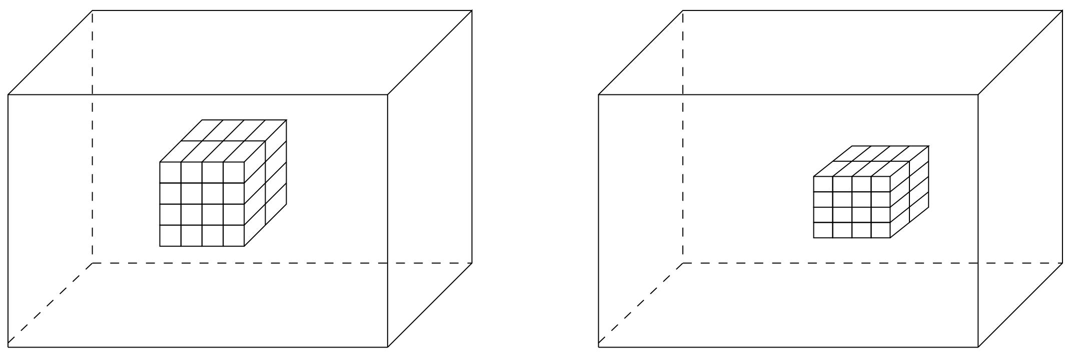
Assume a reference volume $V^{(ref)}(\boldsymbol{x})$ filled with a mesh $\boldsymbol{x}_i^{(ref)}$.

$$E_{\text{Template}} = \frac{1}{N} \sum_i \sum_{\boldsymbol{\Delta x}} F(V^{(ref)}; V, \boldsymbol{x} + \boldsymbol{\Delta x})$$

where the function F might be chosen as

$$F(V^{(ref)}; V, \boldsymbol{x}) = (V^{(ref)}(\boldsymbol{x}) - V(\boldsymbol{x}))^2 \qquad (1)$$

and the sum over $\boldsymbol{\Delta x}$ sums over all voxels within a predefined distance, either radially or in a rectangular region.

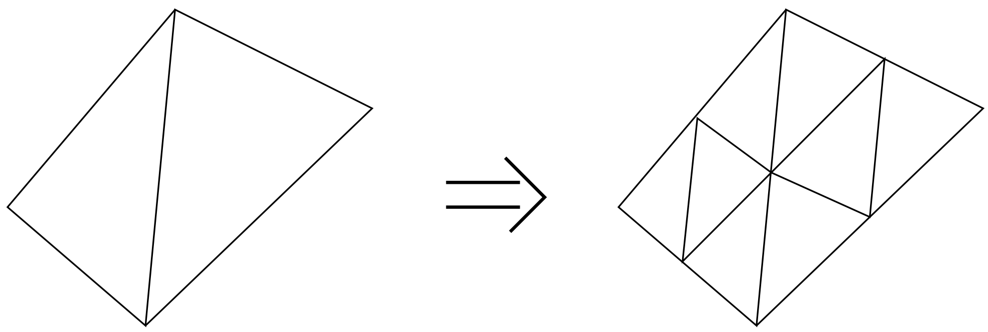


- This term make use of reference volume that has a good surface estimate of the object

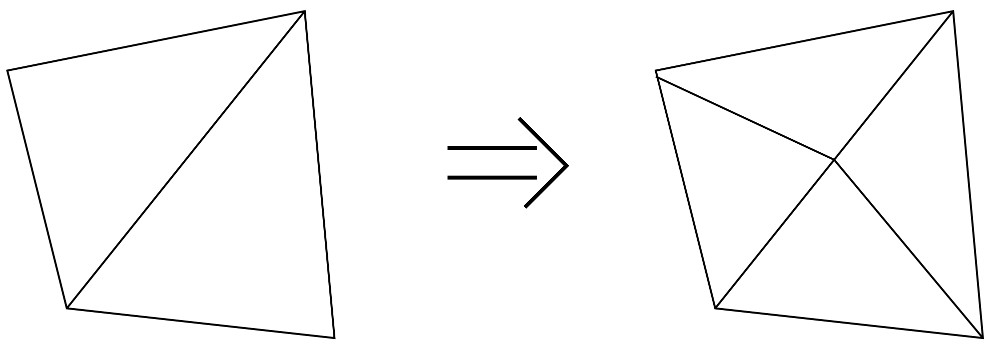
MESH REFINEMENTS

In order to accurately adapt the surface to the object, two mesh refinements are used:

Global refinement



Local refinement



MINIMIZATION

We choose to to compute approximations to the gradient of the energy function by computing the difference in the energy function when moving one vertex a small step.

$$\nabla E \approx \begin{pmatrix} E(\boldsymbol{x}_i + \delta\Delta x) - E(\boldsymbol{x}_i) \\ E(\boldsymbol{x}_i + \delta\Delta y) - E(\boldsymbol{x}_i) \\ E(\boldsymbol{x}_i + \delta\Delta z) - E(\boldsymbol{x}_i) \end{pmatrix} \tag{2}$$

With this approximation to the gradient we can, e.g., use a simple steepest descent algorithm to minimize the energy function,

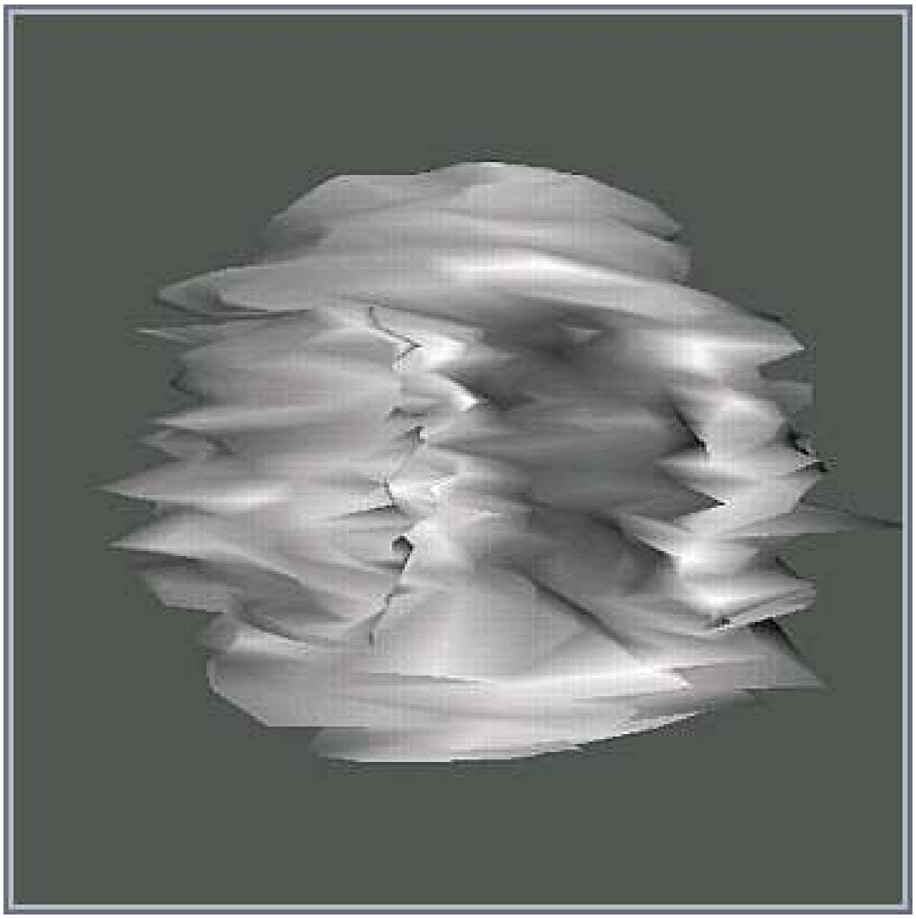
$$\boldsymbol{x}_i^{(t+1)} = \boldsymbol{x}_i^{(t)} - \eta\nabla E$$

The vertex points are selected sequentially either linearly or randomized permutations.

- Alternatives to steepest decent are conjugate gradient or stochastic approaches like simulated annealing.

SNAPSHOTS (TOY EXAMPLE)

The next five images are snapshots from the optimisation procedure where an initial surface is fitted to the boundary of a toy object - an ellipsoid with a rectangular cut.



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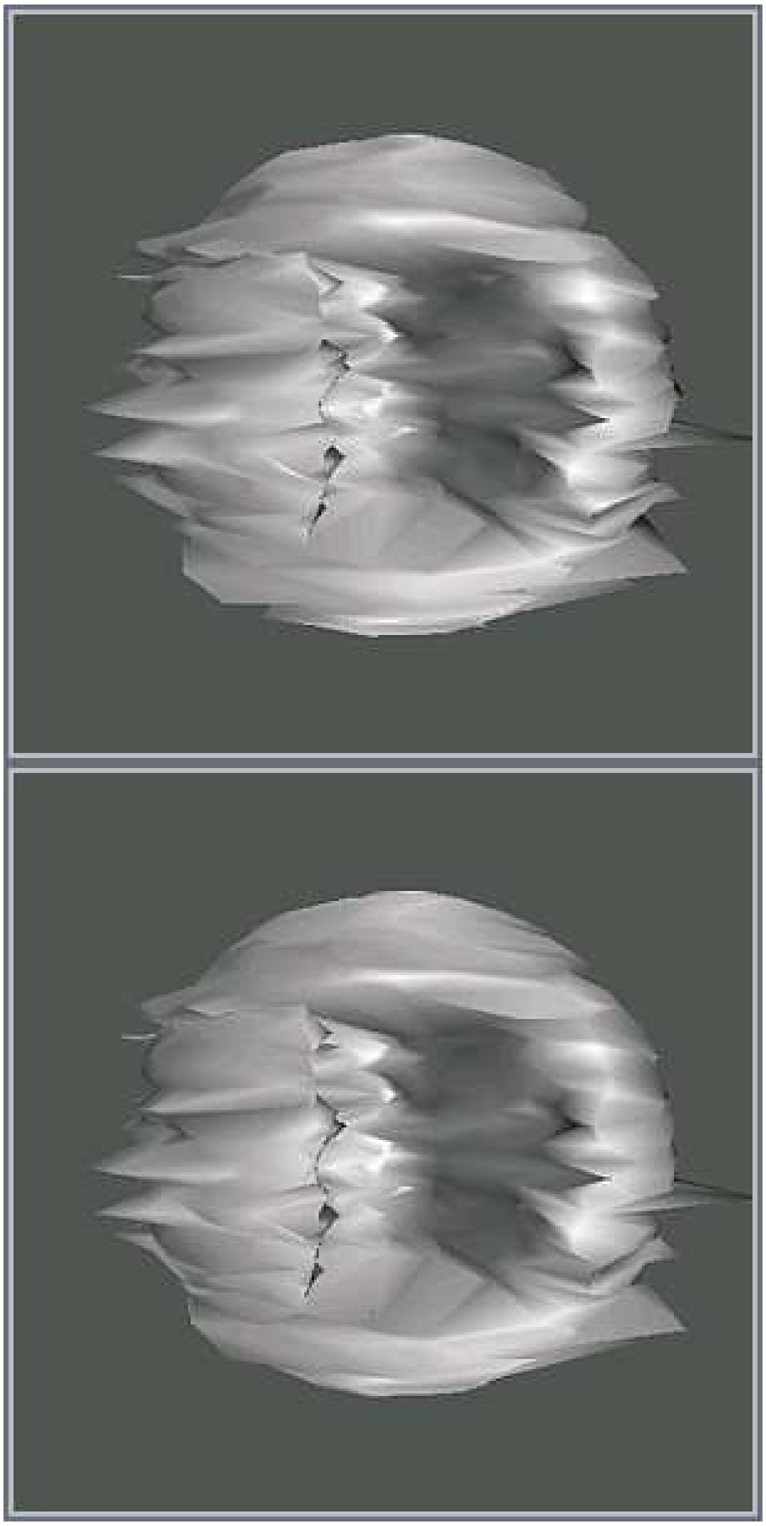

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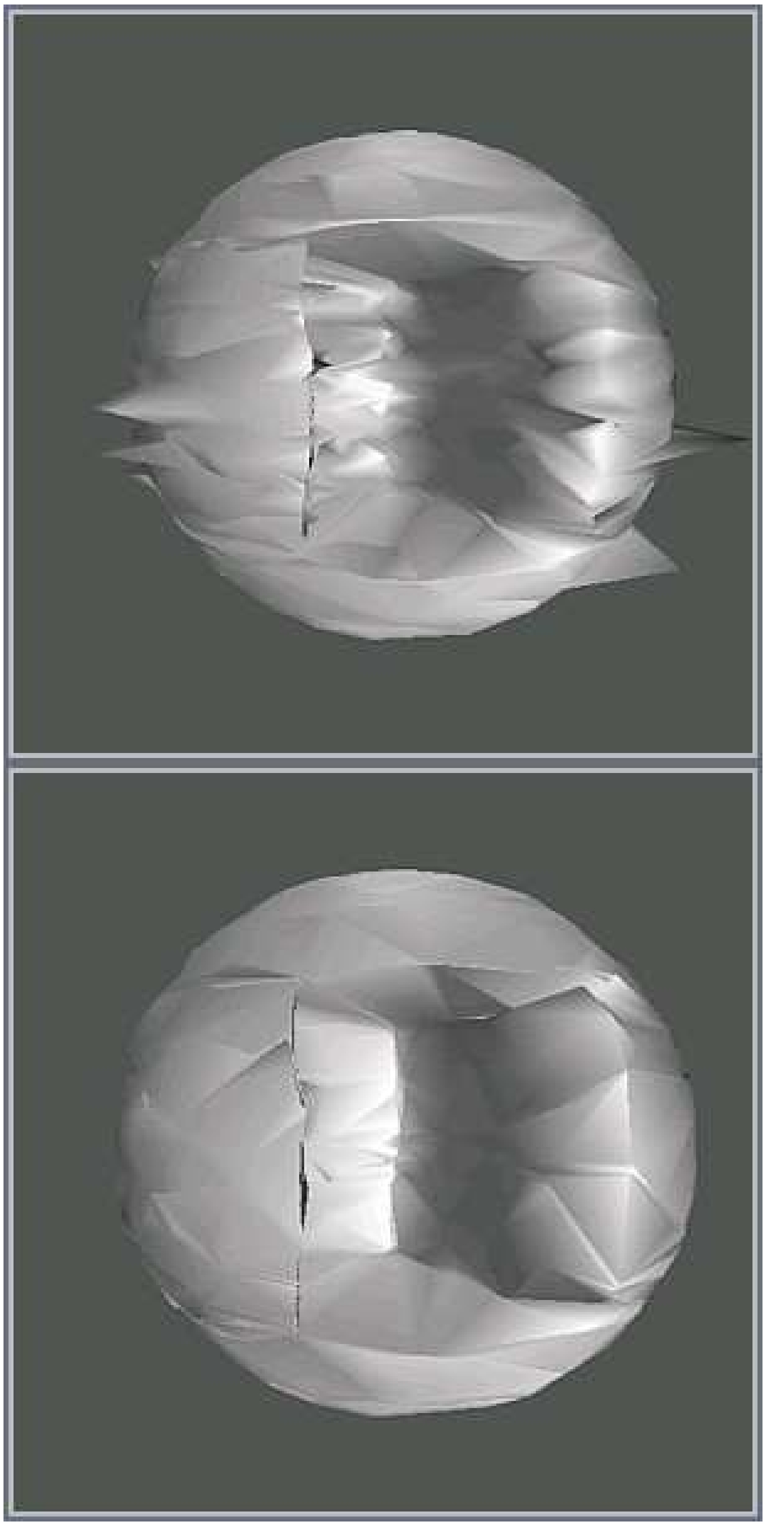

INSTEAD OF A VIDEO! (TOY EXAMPLE)

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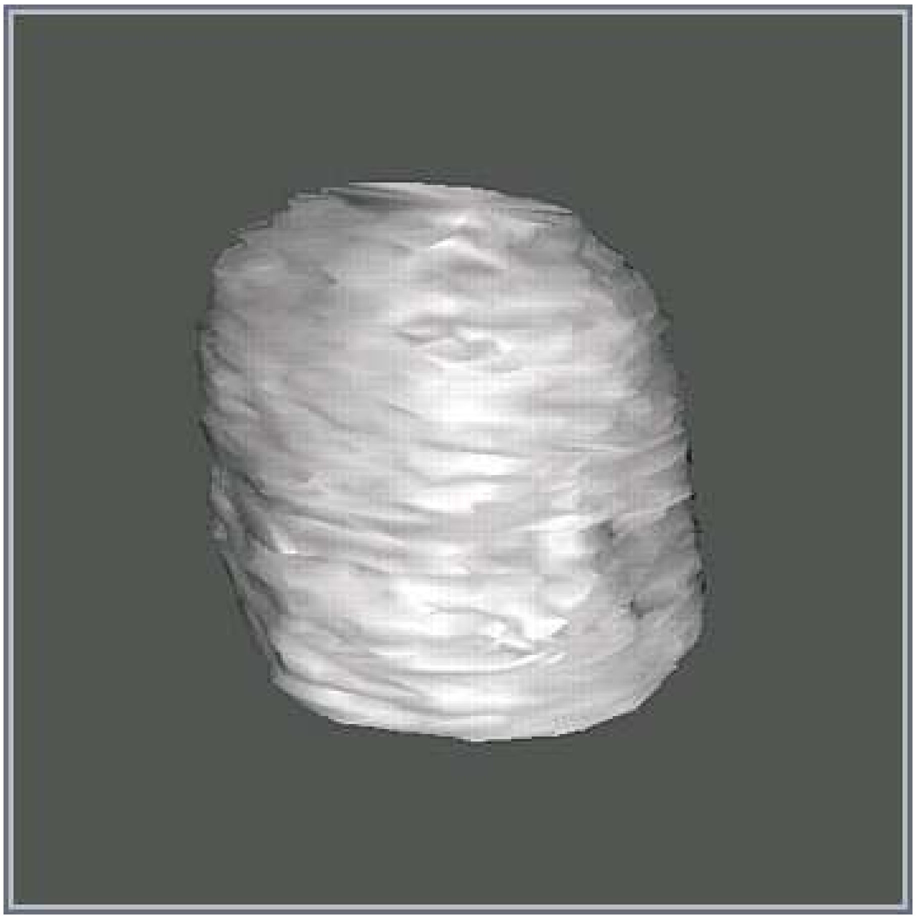
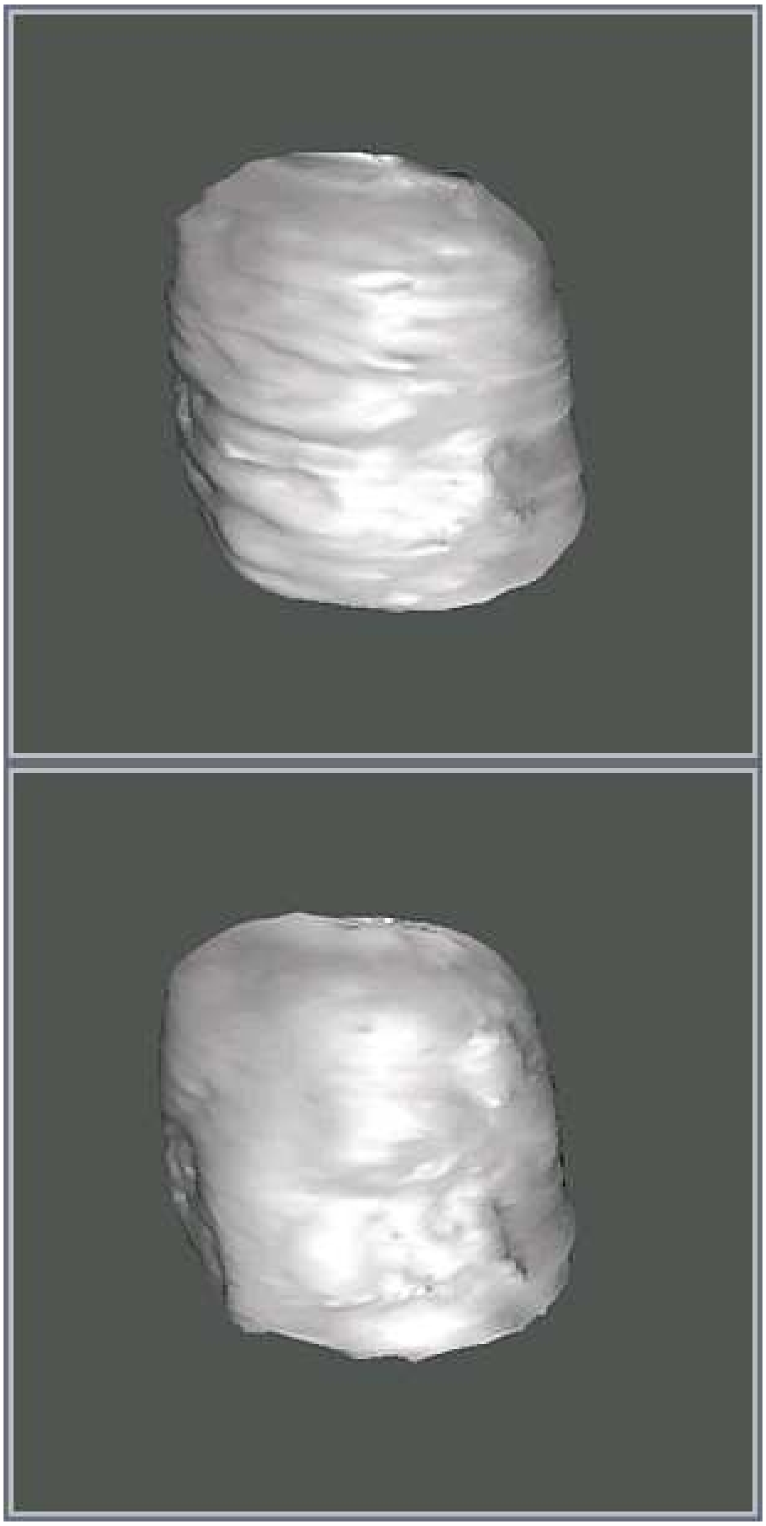
SNAPSHOTS (MRI IMAGE)

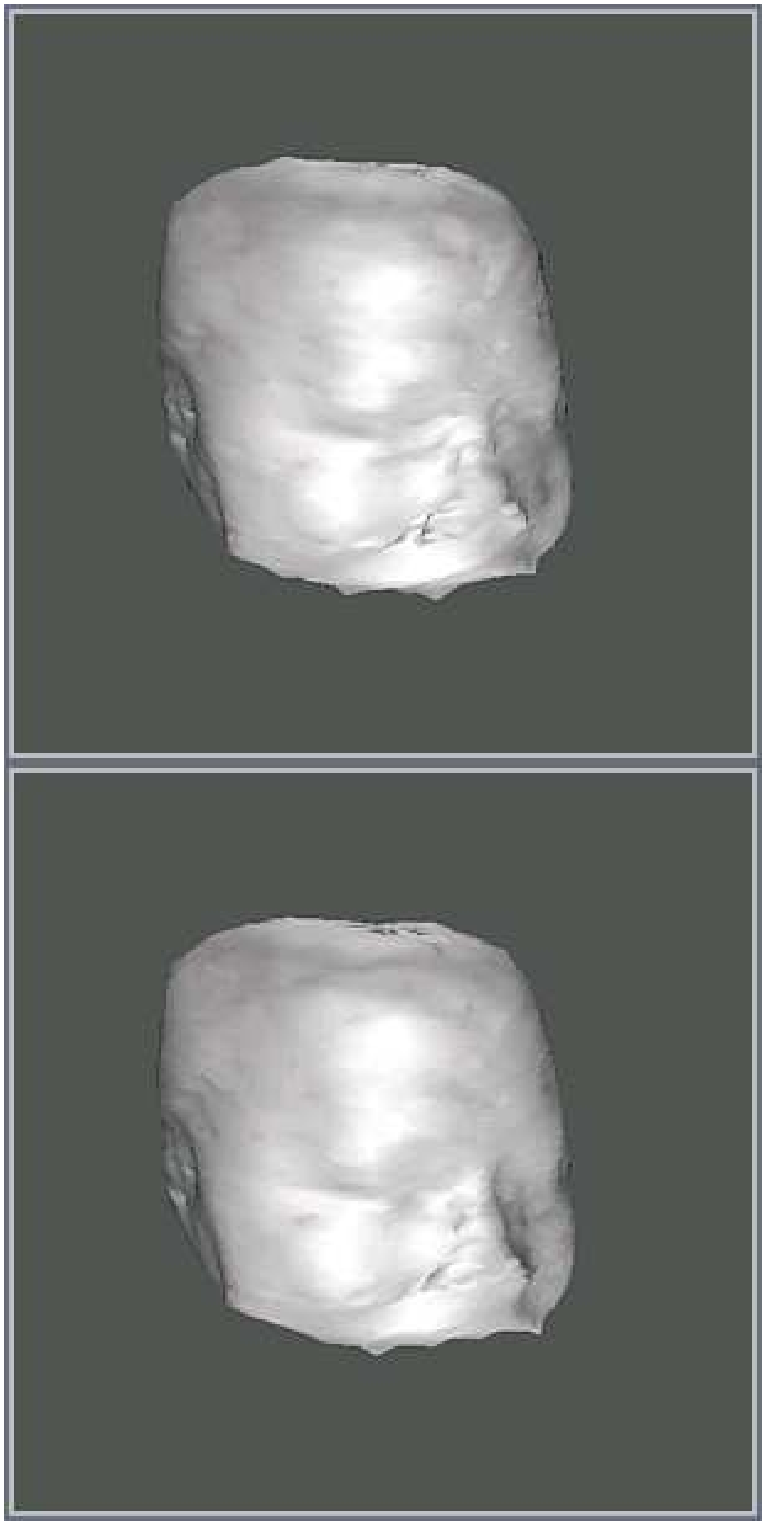
The next five images are snapshots from the optimization procedure where a closed surface is fitted to the outer skull of a MRI image of the human brain.



SNAPSHOTS (MRI IMAGE)



SNAPSHOTS (MRI IMAGE)



INSTEAD OF A VIDEO! (MRI IMAGE)

http://hendrix.imm.dtu.dk/movies/moviehome.html

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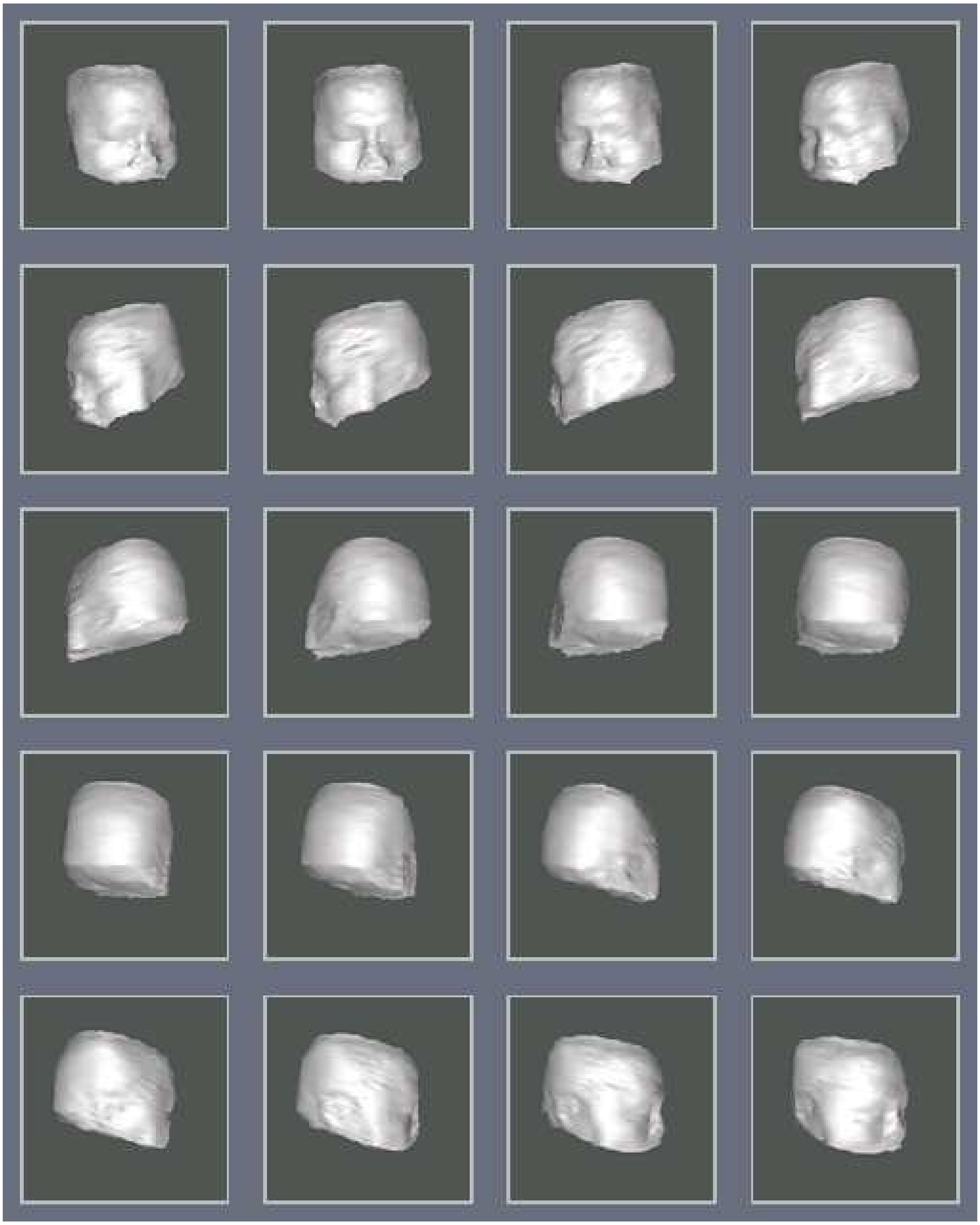

VOLUME RENDERING OF THE SAME VOLUME