Multiple Sclerosis Lesions Segmentation using Spectral Gradient and Graph Cuts

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Plan

- Introduction
- Methodological Framework
  - Spectral Gradient
  - Graph Cut
- Experiments and Results
  - Validation on BrainWeb
  - Influence of the number of seeds
  - Results on real data
- Conclusion

Multiple Sclerosis Lesion Segmentation

- Automatic *vs* manual tools
  - Automatic:
    - \+ Not time consuming for the user (not always for the computer)
    - \+ Capability to handle large cohorts
    - \- Robustness
    - \- Sensitivity to parameters (MRI **and** Algorithm)
  - Manual :
    - \+ Robust and adapted to each patient configuration
    - \- Time consuming for the user
    - \- Sensitivity to the expert

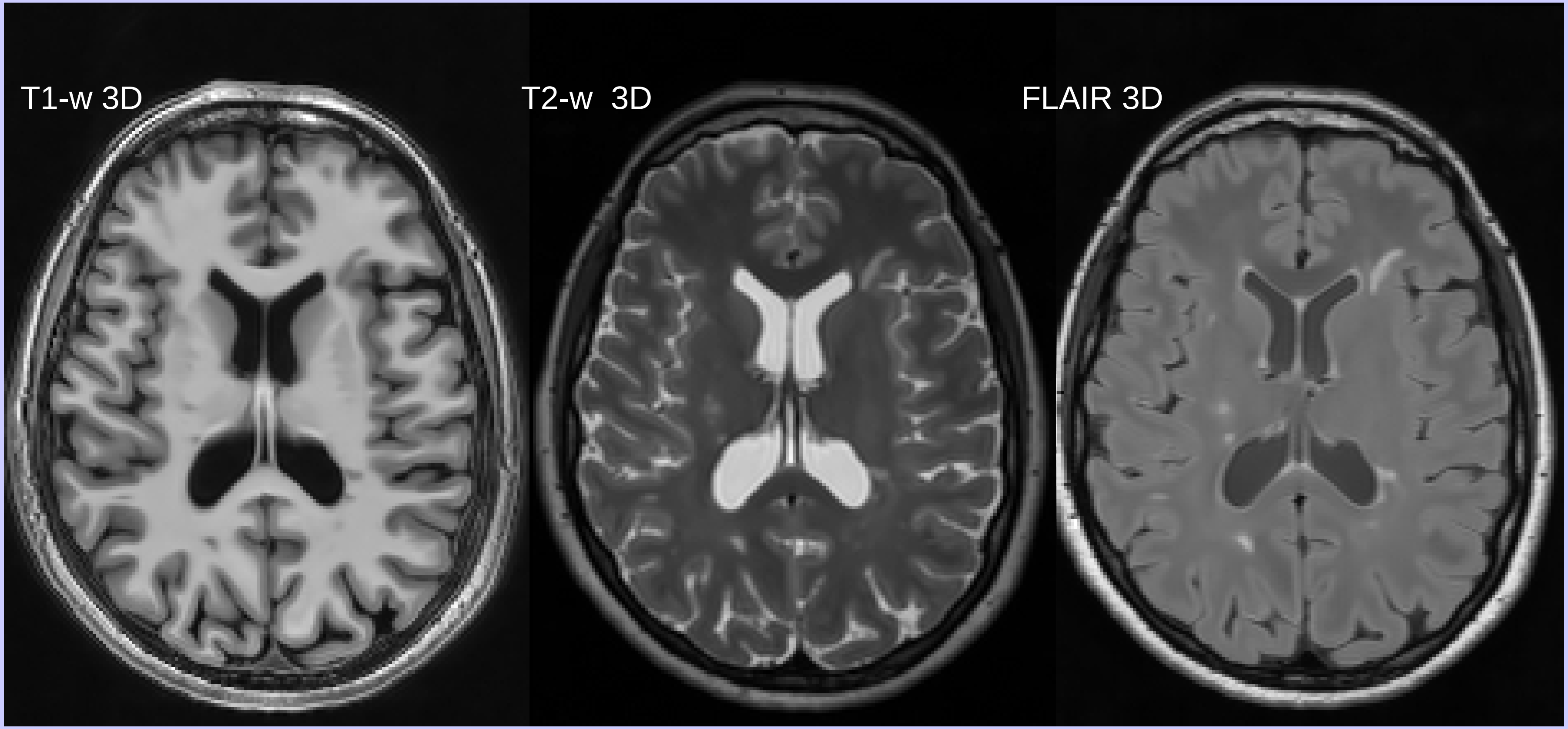
Multiple Sclerosis Lesion Segmentation

- Proposed semi-automatic method
  - \+ Not time consuming for the user (and for the computer)
  - \+ Robust and adapted to each patient configuration
  - \+ Not sensitive to parameters tuning
  - \+ Low sensitivity to the expert

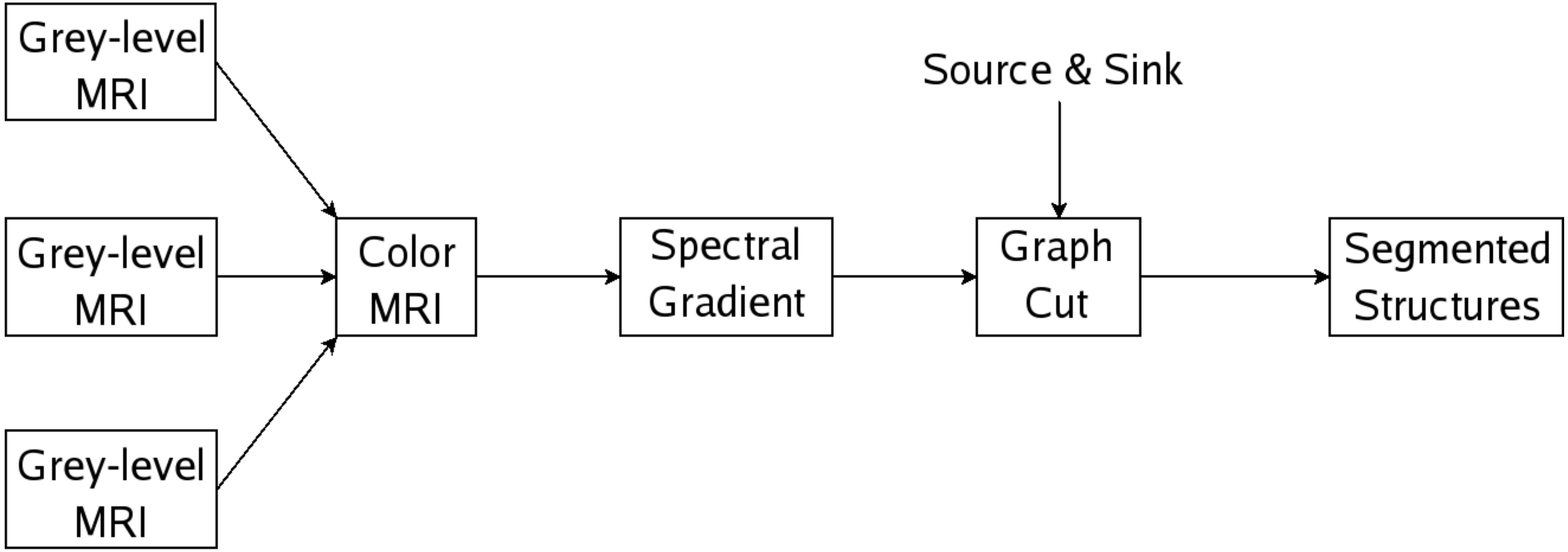
  - \- Not capable to handle large cohorts

Multiple Sclerosis Lesion Segmentation

Generally Based on multiple MRI exams



Proposed Framework



Method Outline:

Segmentation using spectral gradient and graph cut

- Objective : use multisequences MRI and scale space to end-up with fast and semi-automatic segmentation
- Method

1. Create a color image from MRI sequences.
2. Compute the spectral gradient

$$\begin{pmatrix} e \\ e_\lambda \\ e_{\lambda\lambda} \end{pmatrix} = \underbrace{\begin{pmatrix} -0.019 & 0.048 & 0.011 \\ 0.019 & 0 & -0.016 \\ 0.047 & -0.052 & 0 \end{pmatrix}}_{XYZ\ to\ e} \cdot \underbrace{\begin{pmatrix} 0.621 & 0.133 & 0.194 \\ 0.297 & 0.563 & 0.049 \\ -0.009 & 0.027 & 1.105 \end{pmatrix}}_{RGB\ to\ XYZ} \cdot \begin{pmatrix} R \\ G \\ B \end{pmatrix}$$

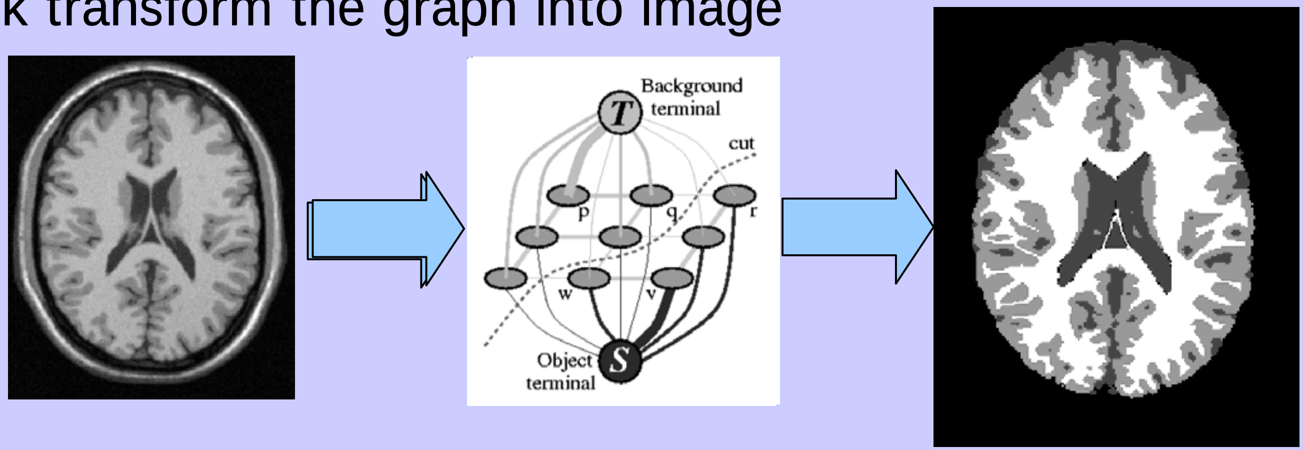
$$\aleph = \sqrt{(\partial_x \varepsilon)^2 + (\partial_y \varepsilon)^2 + (\partial_z \varepsilon)^2 + (\partial_x \varepsilon_\lambda)^2 + (\partial_y \varepsilon_\lambda)^2 + (\partial_z \varepsilon_\lambda)^2}$$

$$\varepsilon =: \frac{e_\lambda}{e}$$

$$\varepsilon_\lambda = \frac{e \cdot e_{\lambda\lambda} - e_\lambda^2}{e^2}$$

[redacted]

5. Back transform the graph into image



STEP 1: Spectral Gradient

Colour Image Formation

– The structure of the spatio-spectral energy distribution depends on 3 functions :

- $c(.)$ spectral reflectance, the "true" color, it does not depend on lighting conditions but on the materiel properties
- $l(.)$ spectrum arriving onto the surface (independent to the position)
- $m(.)$ shading function, influenced by the local geometry
- Then $e(x,y,z,\lambda) = c(x,y,z,\lambda) \times l(\lambda) \times m(x,y,z)$

  describes the formation of a spectral image on a mat object, illuminated by a single light source

Spectral Gradient

- **Retrieve the reflected spectrum from the image**
  - It can be computed by multiplying the colour intensities by two projection matrices :

$$\begin{pmatrix} e \\ e_\lambda \\ e_{\lambda\lambda} \end{pmatrix} = \underbrace{\begin{pmatrix} -0.019 & 0.048 & 0.011 \\ 0.019 & 0 & -0.016 \\ 0.047 & -0.052 & 0 \end{pmatrix}}_{A} \cdot \underbrace{\begin{pmatrix} 0.621 & 0.133 & 0.194 \\ 0.297 & 0.563 & 0.049 \\ -0.009 & 0.027 & 1.105 \end{pmatrix}}_{B} \cdot \begin{pmatrix} R \\ G \\ B \end{pmatrix}$$

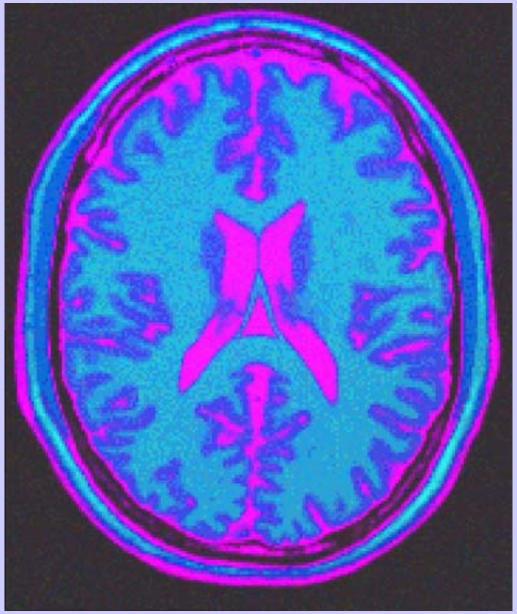
    - The matrix A transforms the RGB measures into the CIE 1964 XYZ space, often used in colour imaging applications
    - The matrix B is the best linear transform from XYZ to Koenderink Gaussian colour model [Koenderink-98]

Spectral Gradient

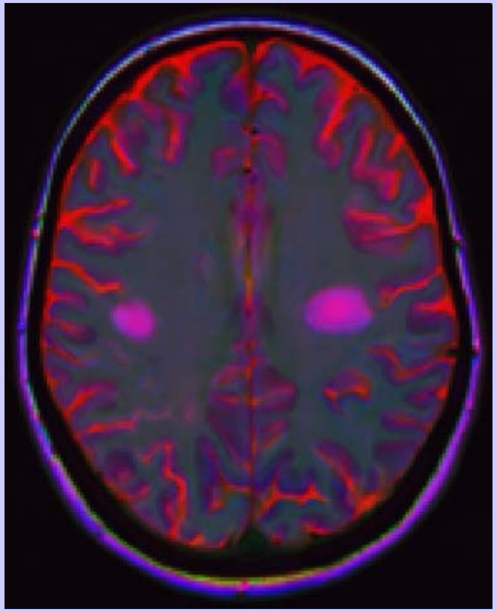
Application to multichannel Color MRI

– Each MRI sequence is set to one of the R, G or B channel:

R = T1
G = T2
B = PD



R = T1
G = T2
B = Flair



Spectral Gradient

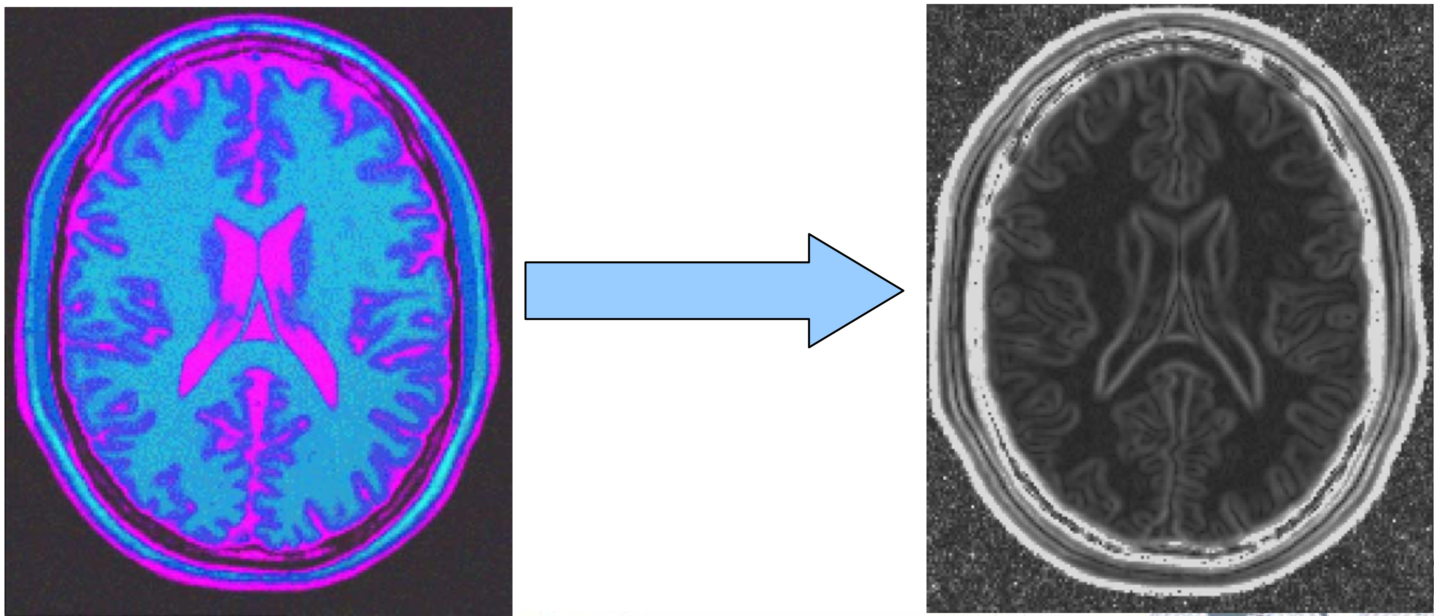
- **Colour edge detectors**
  - First order operator : $\varepsilon = \frac{1}{e} \cdot \frac{\partial e}{\partial \lambda} = \frac{e_\lambda}{e}$
    - Its spatial gradient detects blue-yellow transitions
  - Second order operator: $\varepsilon_\lambda = \frac{\partial \varepsilon}{\partial \lambda} = \frac{e \cdot e_{\lambda\lambda} - e_\lambda^2}{e^2}$
    - Its spatial gradient detects green-purple transitions

➔ We get Scale Space operators (derivatives are obtained by Gaussian convolutions with σ as spatial parameter)

Spectral Gradient

Results

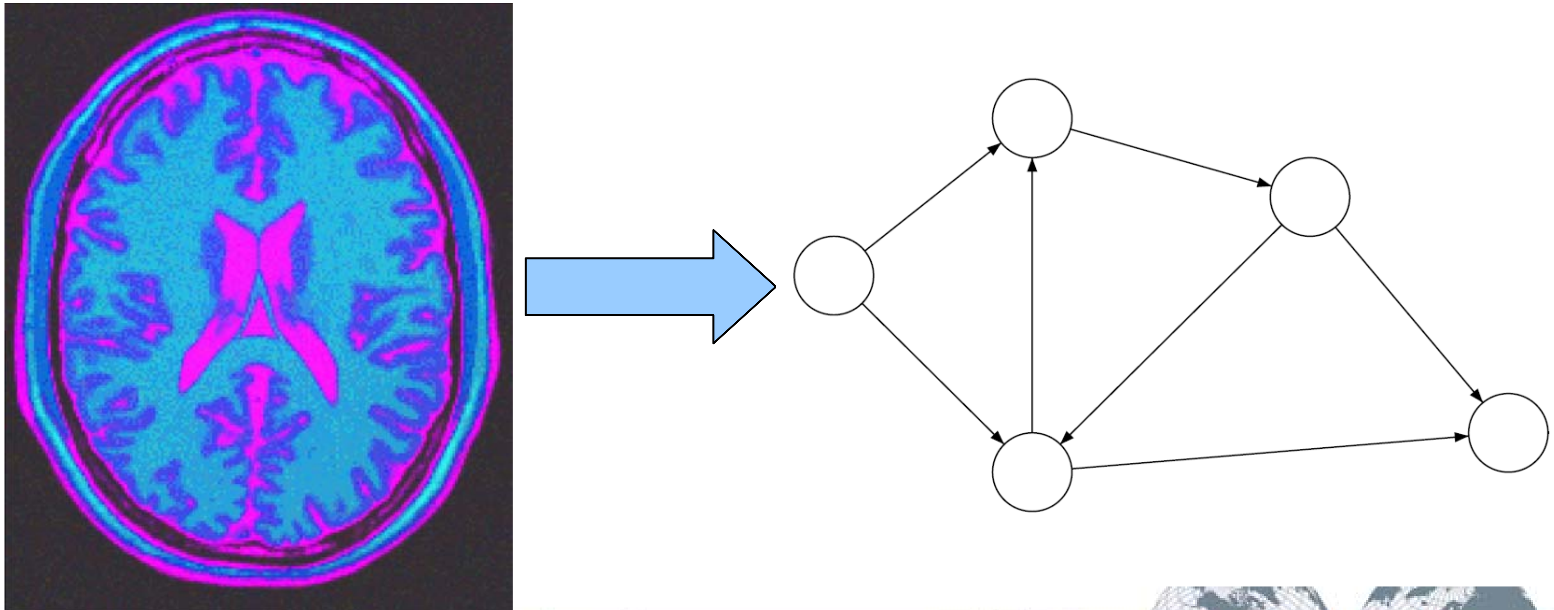
- Application of the first and second order operators with $\sigma=1$ (enhanced the thin edges) :



STEP 2: Graph Cut

From Image to Graph

Voxels	=>	Nodes of the graph
Neighbour similarity	=>	Edges of the graph
Segmentation	=>	Partition of the graph



Graph Cut

From Image to Graph

- Two special nodes (the terminal nodes):
  - The source (*ie* the object to segment)
  - The sink (*ie* everything else)
- The edges from a terminal node to a voxel depends on the similarity between this voxel and one of the two classes
  - neighbouring edge (N-link)
  - terminal edge (T-link)

Proposed Graph Cut

Semi-automatic method

1. Source- and sink- seeds are selected
2. Computation of a parametric model (Gaussian pdf) for each class from the given seeds
3. T-link values between a voxel v and the $Source$ is

$$R_{v,Source} = -\ln P(I_v | Sink)$$

4. T-link value between a voxel v and the $Sink$ is

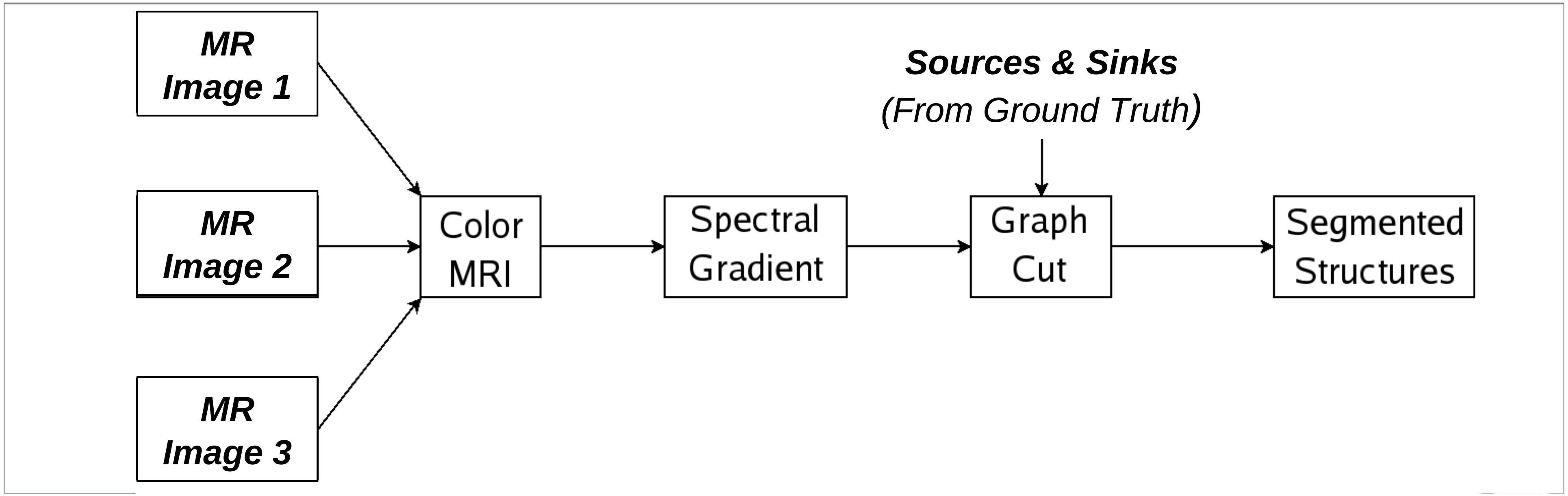
$$R_{v,Sink} = -\ln P(I_v | Source)$$

5. N-link value between a voxel u and a voxel v is:

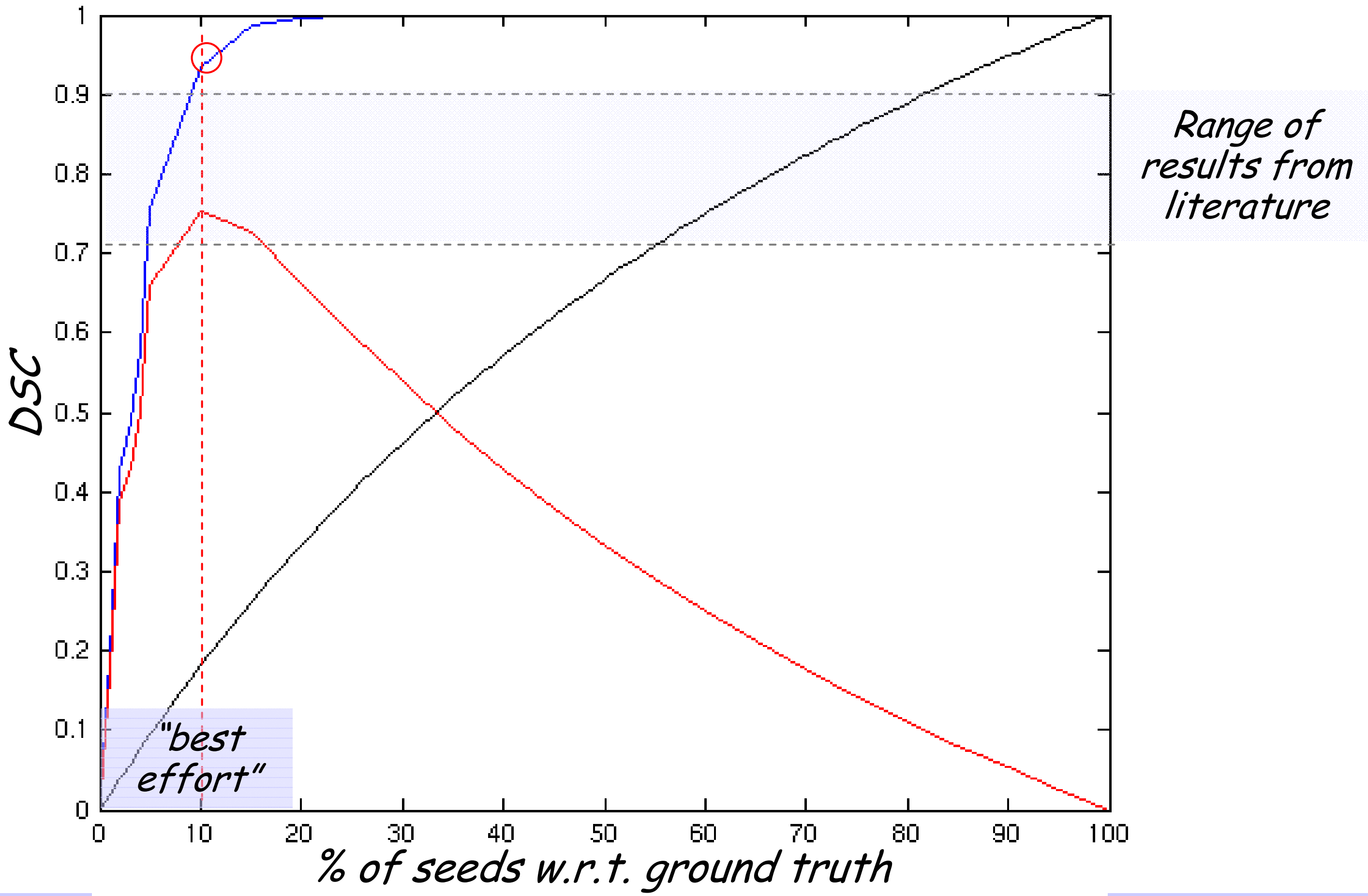
$$B_{u,v} = \exp \frac{-SpectralGradient(u,v)}{2\sigma^2}$$

Experiments and Results

- Framework
  - Test on synthetic data : BrainWeb
  - Test on clinical data (ground truth coming from experts)
    - 3 sets of data (T1-w, T2-w, PD); (T1-w, T2-w, FLAIR) and (T1-w, gd-T1, FLAIR)
  - Sources and Sinks are defined by the ground truth:
    1. Random decimation of the ground truth
    2. Erosion decimation of the ground truth



Validation on Brainweb (T1w, T2w, PD)

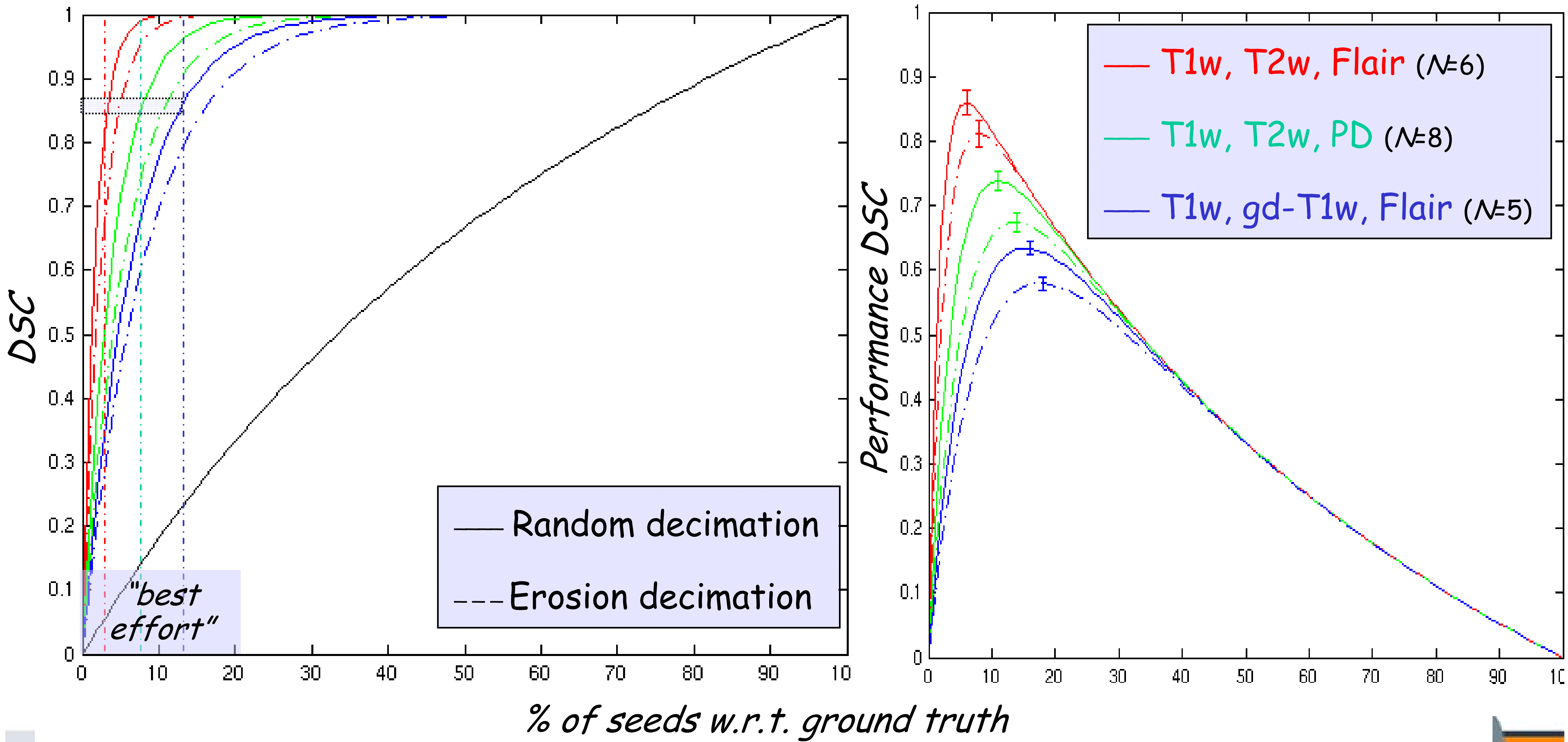


Blue line : DSC = f(seeds)

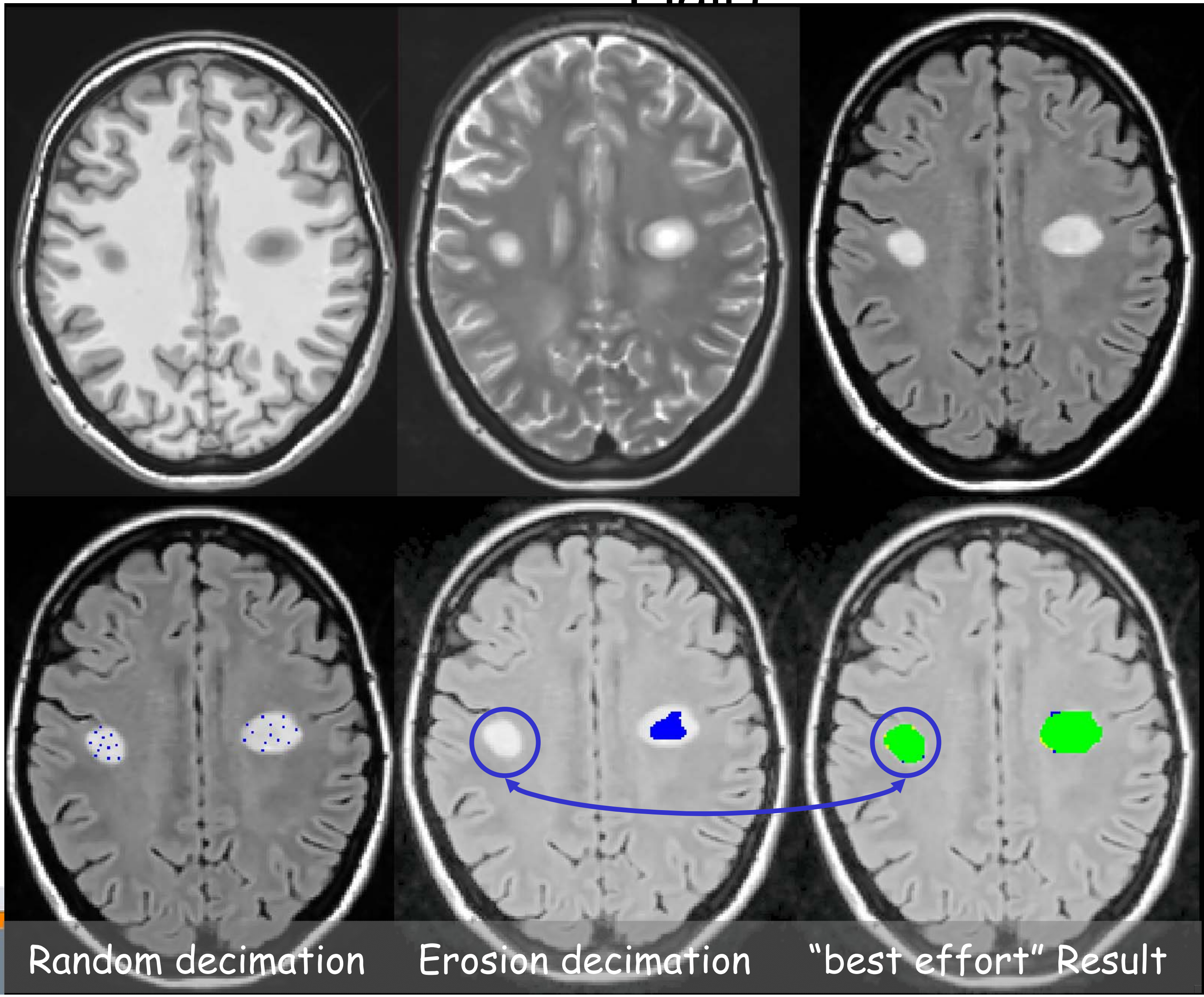
Black line : DSC from initialization seeds only (no input from the algorithm).

Red Line : Performance (i.e. difference between the two preceding curves)

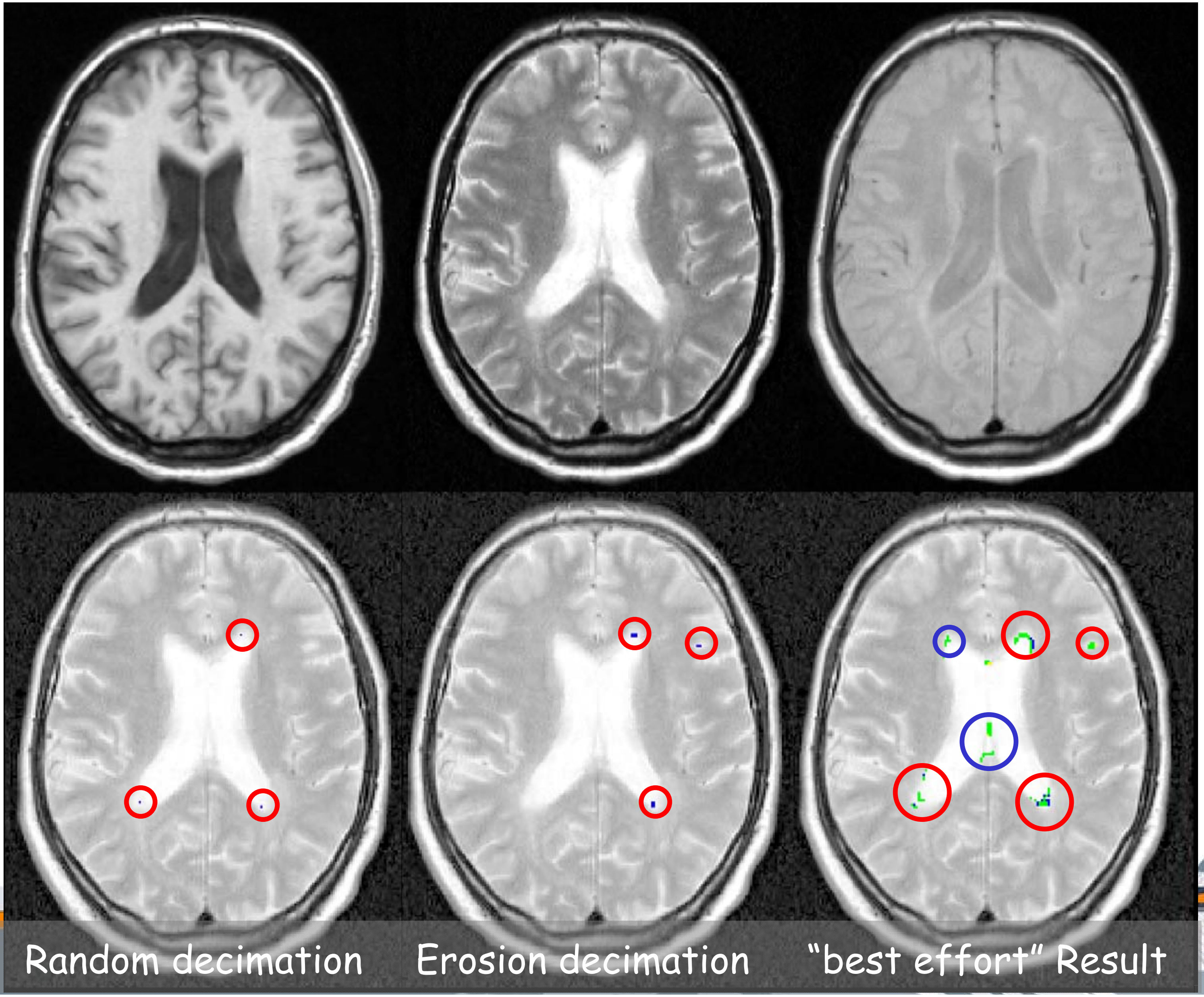
Average Results on clinical Data



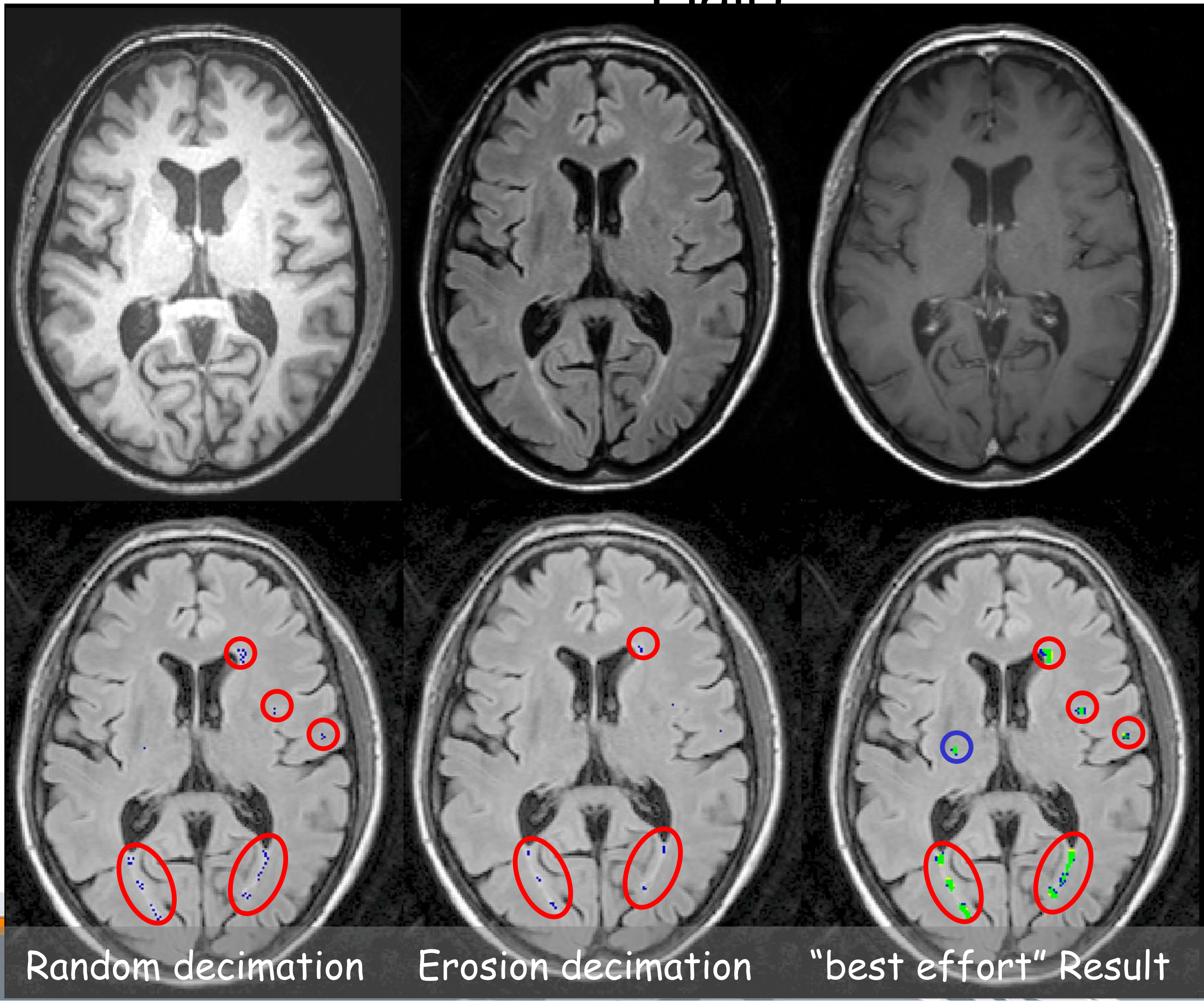
Results on clinical data (T1w, T2w, Flair)



Results on clinical data (T1w, T2w, PD)

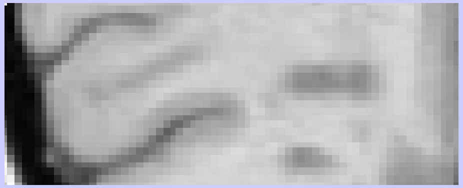


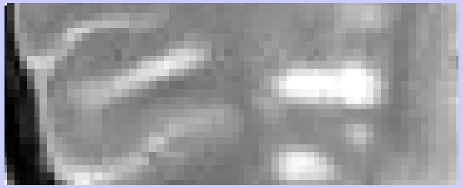
Results on clinical data (T1w, gd-T1w, Flair)

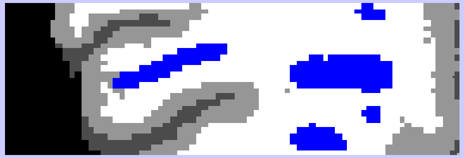


Results on clinical data

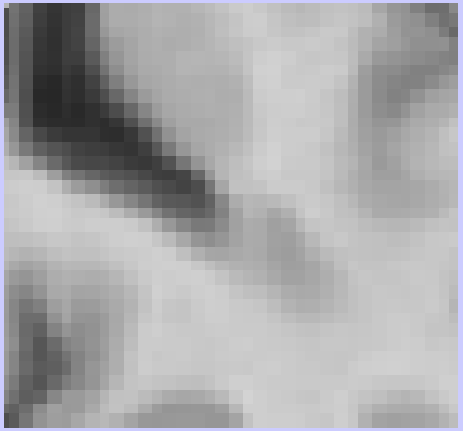
Zoom out on MS Lesions

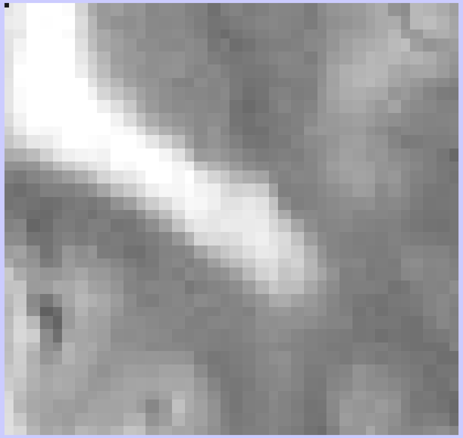


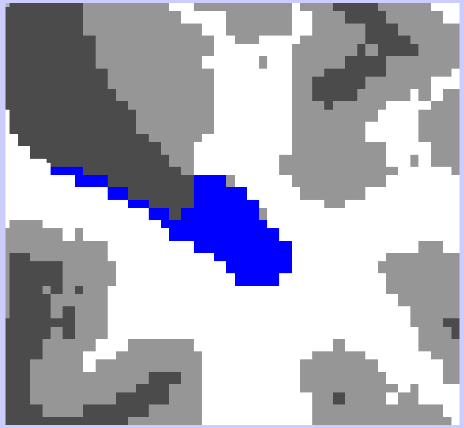




T1w T2w Segmented Classes







Conclusion & Perspectives

- Method
  - New multidimensional framework combining Spectral Gradient and Graph Cut
  - Efficient (~1min on laptop) semi-automatic MS lesion segmentation
  - Limited initial effort for the user
  - Robust to data and protocols (evaluated on {T1, T1-Gd, Flair} , {T1, T2, PD}, and {T1, T2, Flair})
  - Graph Cut framework allows fast interactive update
- Perspective
  - Could be initialized by an automatic tissue classification (for processing of large collections)
  - Optimization of “colour model” parameters
  - Performance on longitudinal MS data?