MS Lesion Segmentation using Markov Random Fields

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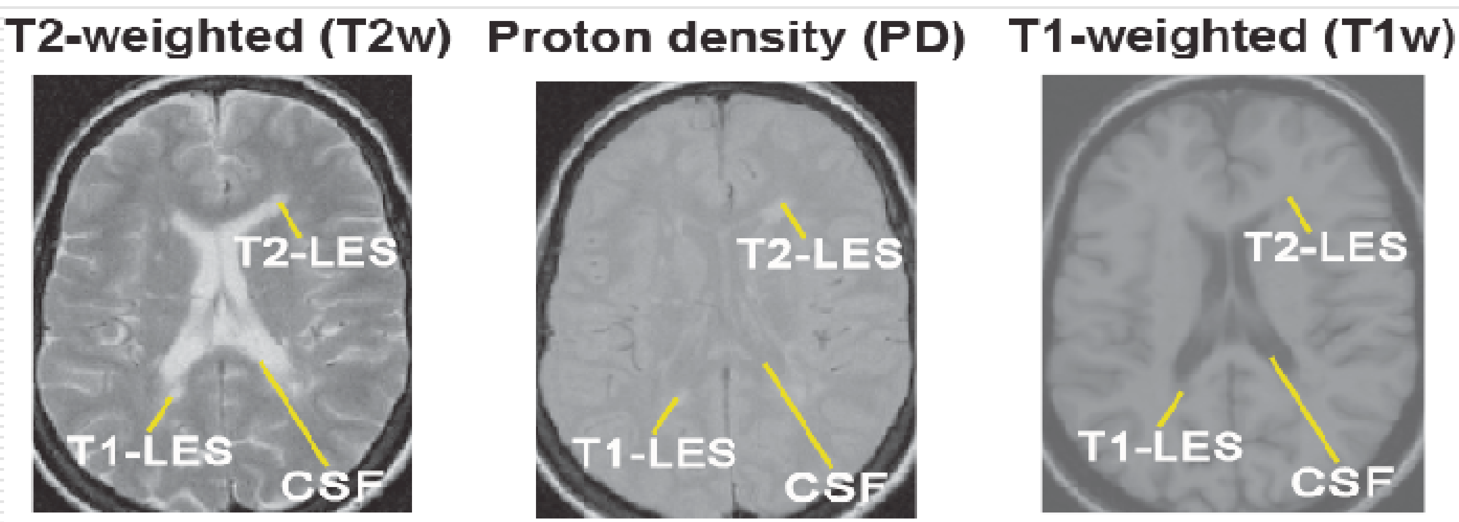
Mohak Shah

Outline

- Problem Context
- Automatic Lesion Detection Approaches
- A complete MRF based approach
- Empirical Results
- Conclusion and Future work

Problem Context

- MS Lesions
  - hyper-intense w.r.t. WM in T2w
  - hypo-intense w.r.t. WM in T1w
- PDw helps in distinction from CSF
- Multispectral space (T1w, T2w, PDw) = **I**



Approaches to Automatic Detection

- Various Approaches
  - Contouring (Grimaud *et al*. 1996), Fuzzy Reasoning (Udupa *et al*. 1997), connected component analysis (Ge *et l*. 2001), atlas-based (Al-Zubi *et al*. 2002), geometric models (Yang *et al*. 2004), clustering (Francis, 2004), Spectral gradients and graph cuts (Lacoeur *et al*. 2008)

- Model based approaches: Lesions as outliers
  - Van Leemput *et al.* (2001)

- Markov Random Fields (MRFs) (Harmouche, 2006)
  - Bayesian approach: MRF applied *after* labeling solution obtained

Motivation

- Multi-spectral intensities can model the tissue behavior relatively accurately
- Local contextual information
  - Francis 2004, Harmouche, 2006
- Probabilistic Approach useful
- **Proposed Approach:** Explicit lesion modeling in MRFs

Understanding MRFs

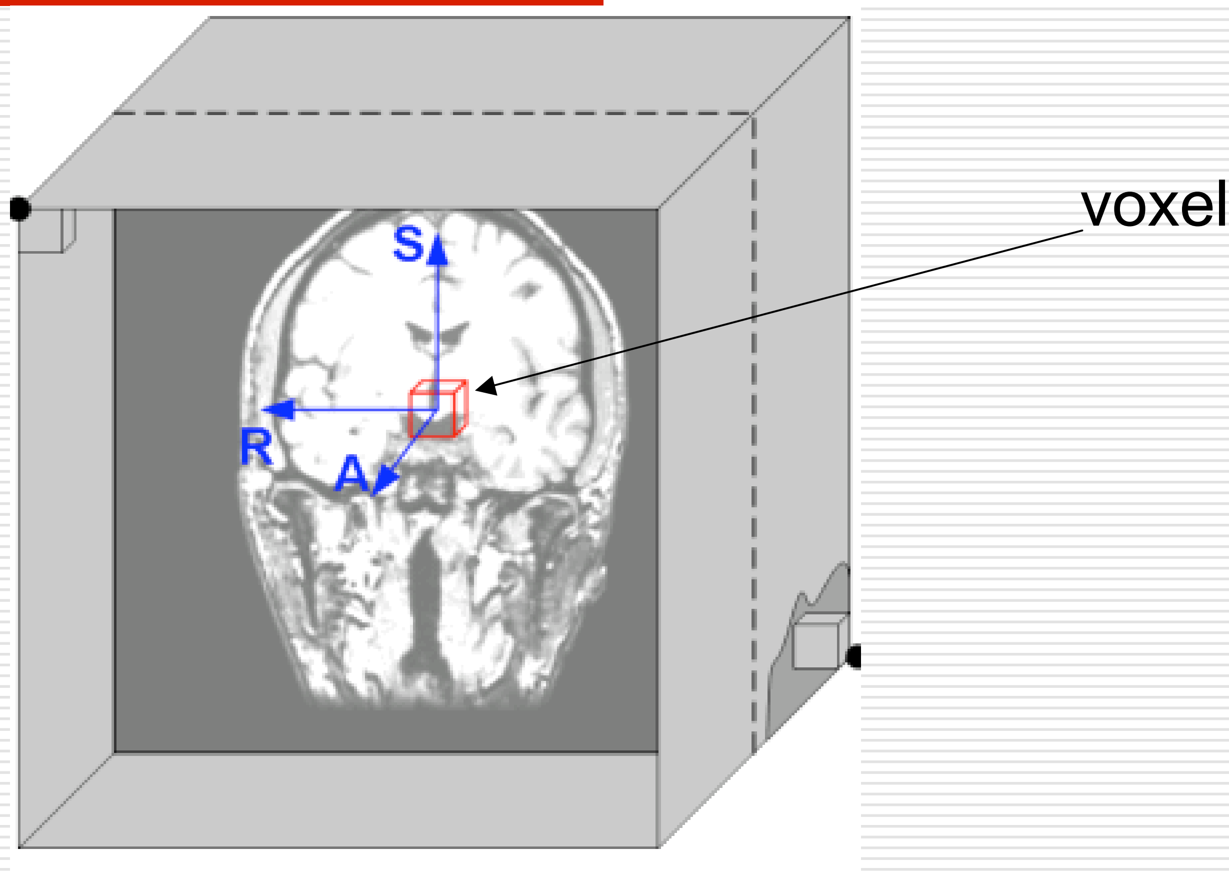
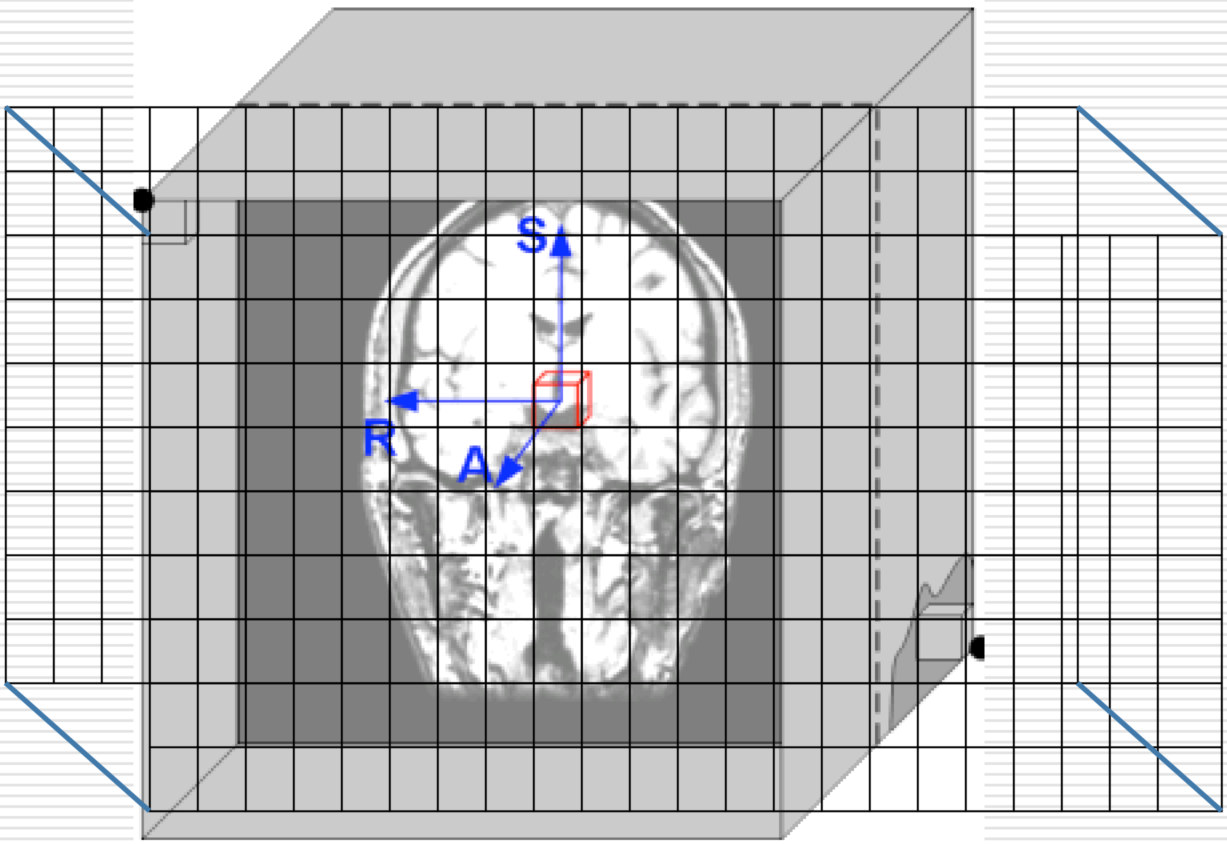
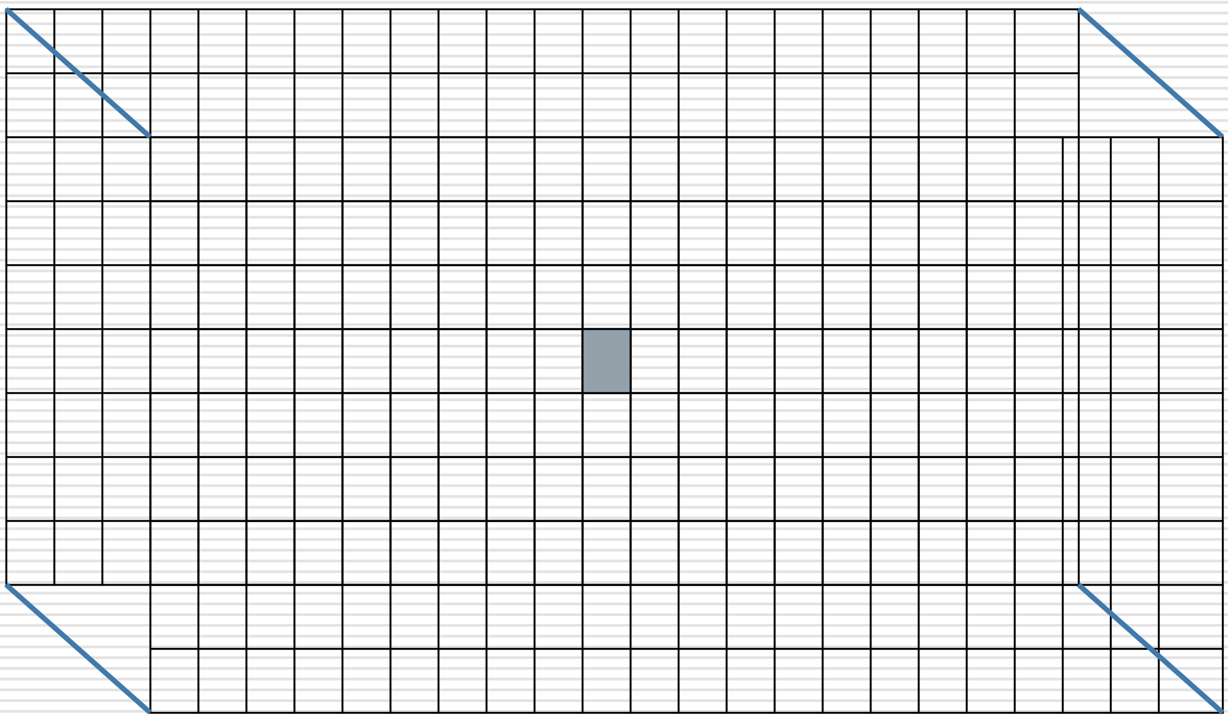


Image Source: Understanding Freesurfer, Its Process and Data, http://www.wideman-one.com

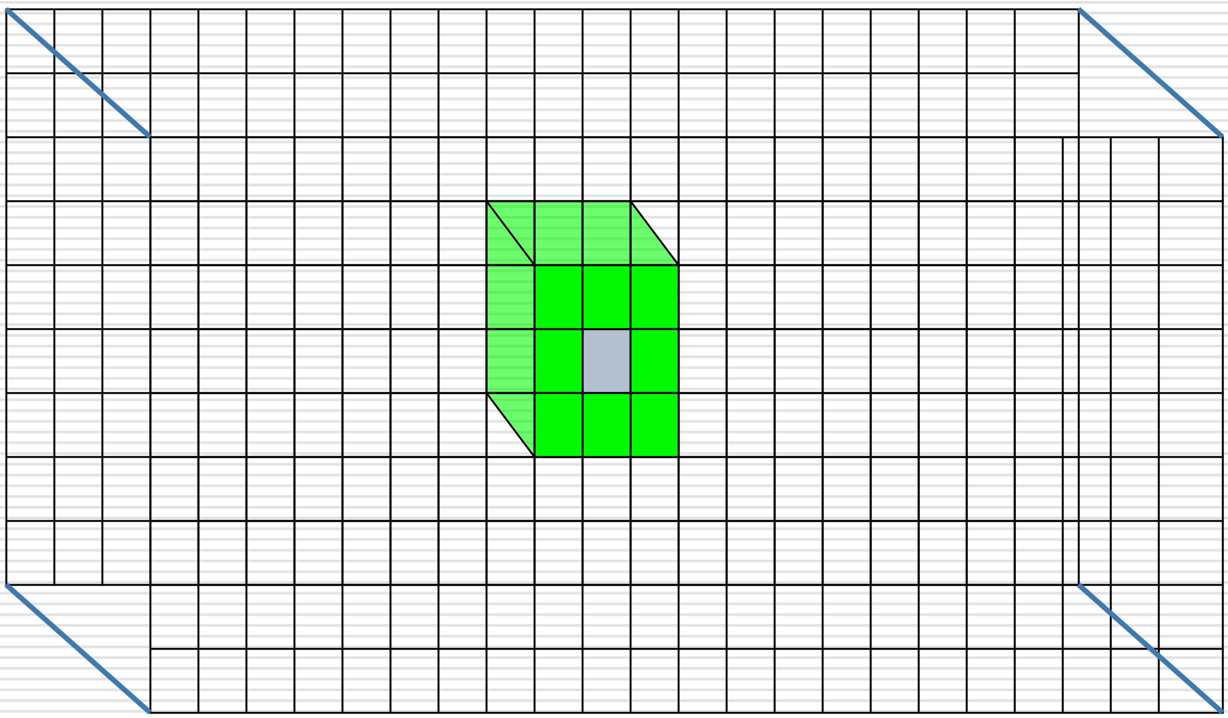
Understanding MRFs



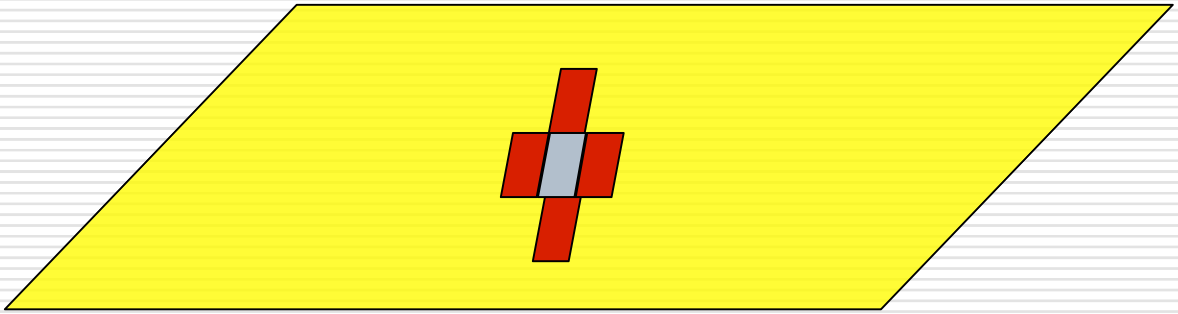
Understanding MRFs: A voxel



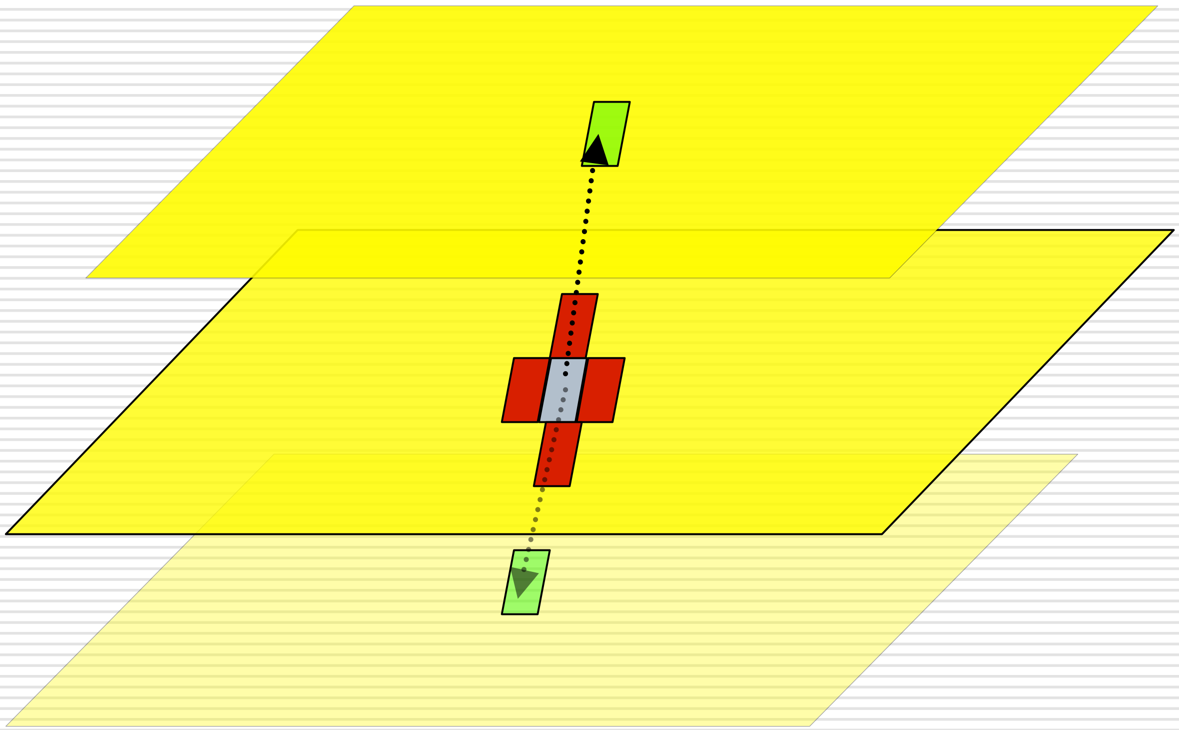
Neighborhood



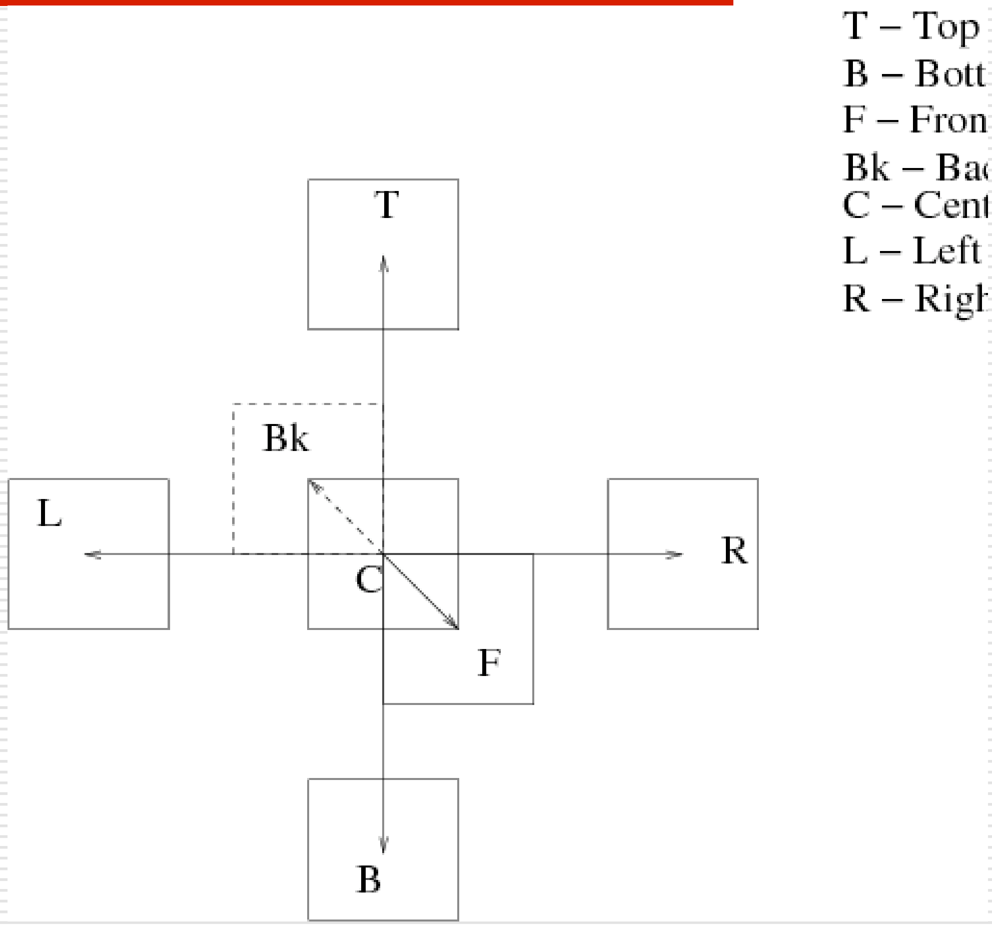
Sub-neighborhood



Sub-neighborhood

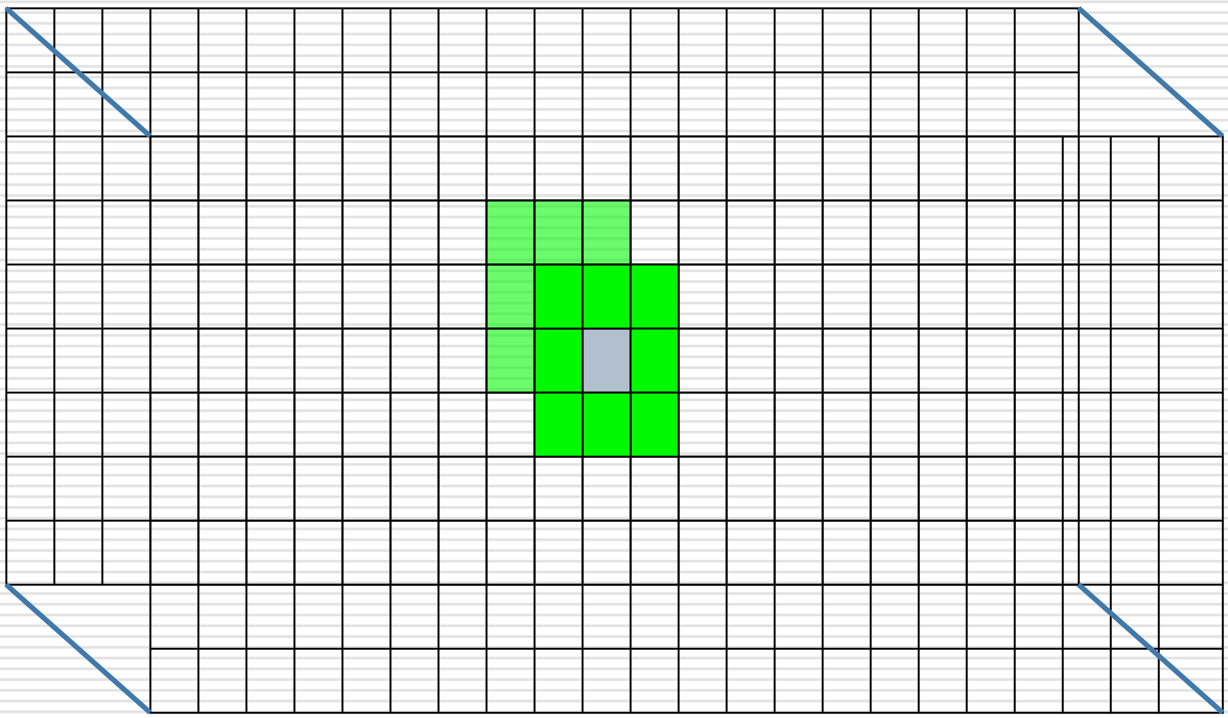


A 7-voxel Clique



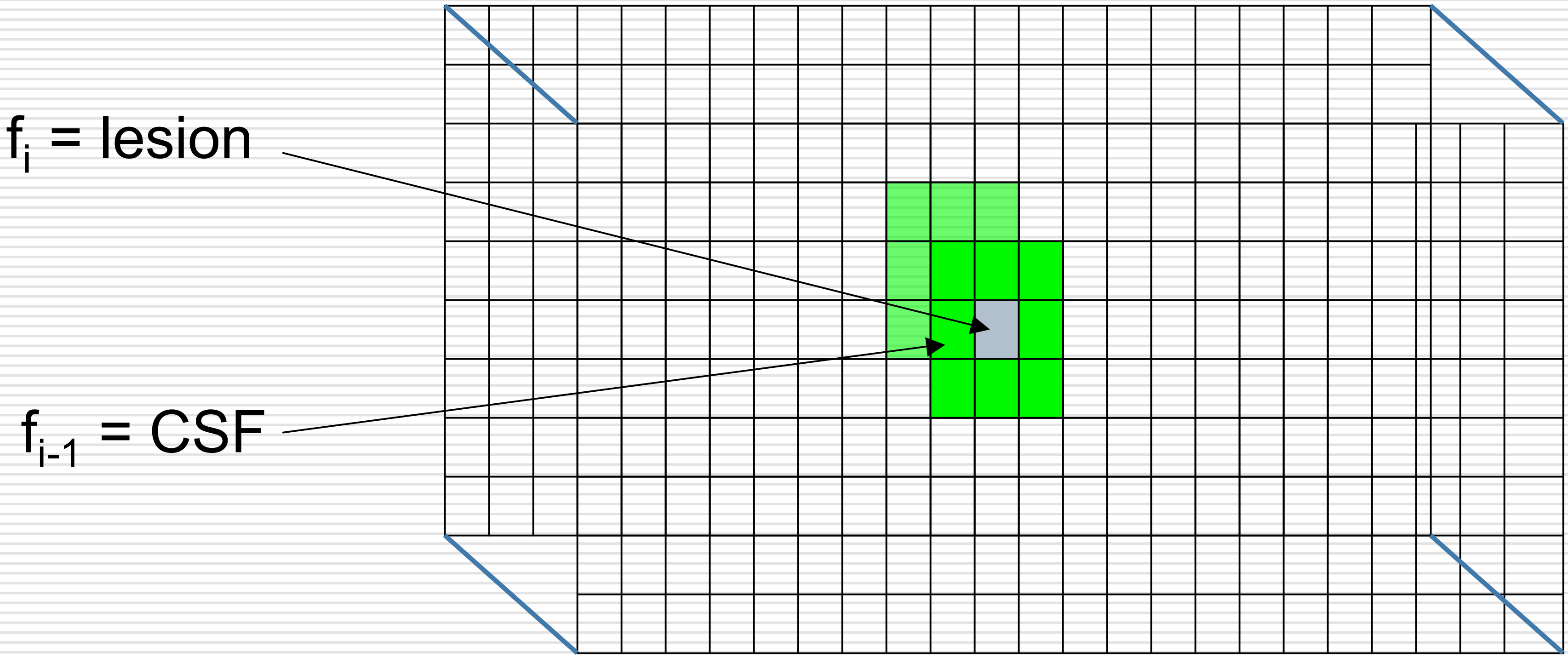
Label Assignments

- Let $\mathbf{f} = (f_1, f_2, \ldots, f_n)$ be a label assignment



Label Assignments

- Let **f** = $(f_1, f_2, \ldots, f_n)$ be a label assignment
- Many such **f**'s possible



Modeling Label Assignments

- The **f**'s can be modeled as a Gibbs distribution

$$P(\mathbf{f}) = \frac{1}{\sum_{\mathbf{f} \in \mathcal{F}} exp(-\frac{1}{T}U(\mathbf{f}))} exp(-\frac{1}{T}U(\mathbf{f})) \quad (1)$$

Modeling Label Configurations

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Energy Function

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- Minimize U(**f**) to Maximize P(**f**)

The Energy Function

- U(**f**) takes into account
  - voxel intensity behavior (1-voxel clique); and
  - local (sub-)neighborhood information (7-voxel clique)
- Clique sizes
  - compromise between the amount of neighborhood info and computational complexity

The Energy Function: Characterizing Neighborhoods

- Characterize 1-voxel cliques
  - Gaussian Assumption over tissue intensity behaviors

- Characterize nature of 7-voxel cliques
  - Homogenous (Positional Independence)
  - Isotropic (Orientational Independence)

The Energy Function

$$U(\mathbf{f}) = \sum_{i=1}^{n} \left[(\mathbf{I}_i - \mu_{f_i})^T \Sigma_{f_i}^{-1} (\mathbf{I}_i - \mu_{f_i}) + \sum_{\forall j, j \in N_i} \alpha(\mu_{\mathbf{f_i}} - \mathbf{I_j})^2 + \beta m(f_i) \right] \quad (1)$$

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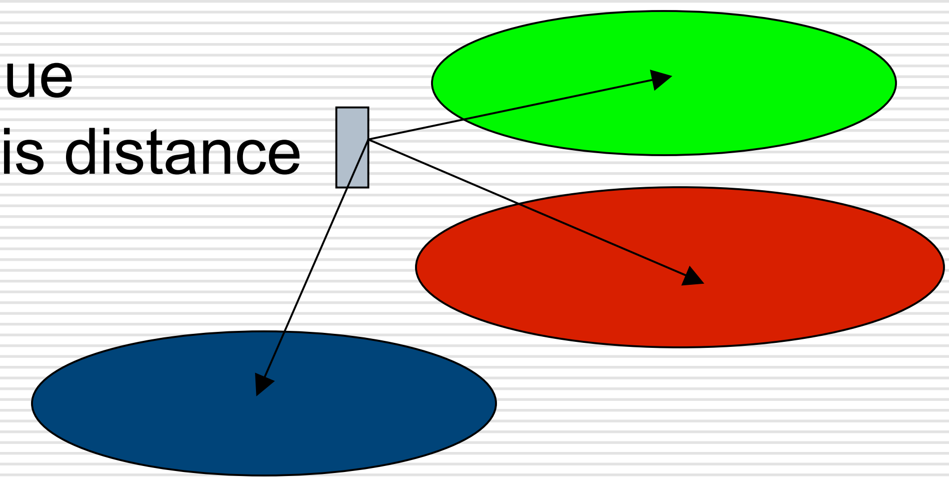
1-voxel clique
Mahalanobis distance



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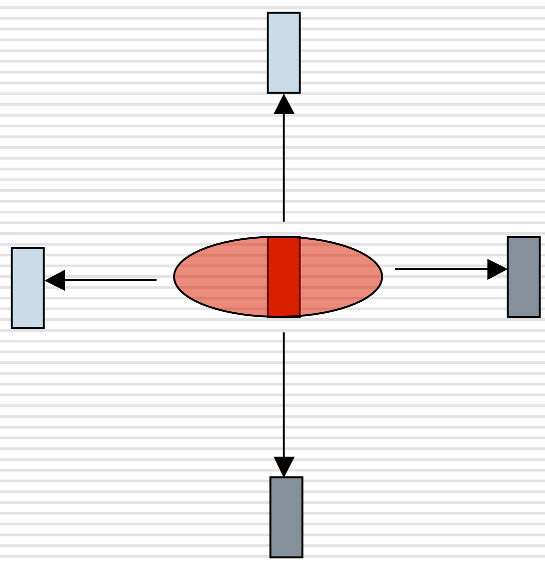
7-voxel clique
Gradient



The Energy Function

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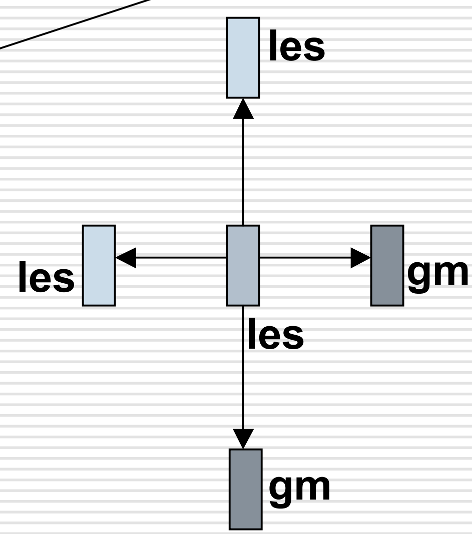
7-voxel clique
Like-neighbors



The Energy Function

$$U(\mathbf{f}) = \sum_{i=1}^{n} \left[(\mathbf{I}_i - \mu_{f_i})^T \Sigma_{f_i}^{-1} (\mathbf{I}_i - \mu_{f_i}) + \sum_{\forall j, j \in N_i} \boxed{\alpha} (\mu_{\mathbf{f_i}} - \mathbf{I_j})^2 + \boxed{\beta} m(f_i) \right] \tag{1}$$

Control Parameters

The Algorithm

- Use a set of training MRI volumes to obtain distributions of individual tissue types
  - Labels: WM, GM, CSF, T1les, T2les, Bkg
- Train the algorithm to estimate control parameters α and β
- For any new MRI volume, apply MRF algorithm with α and β from training
- Optimize over **f** using Simulated annealing
- Smooth using b-splines

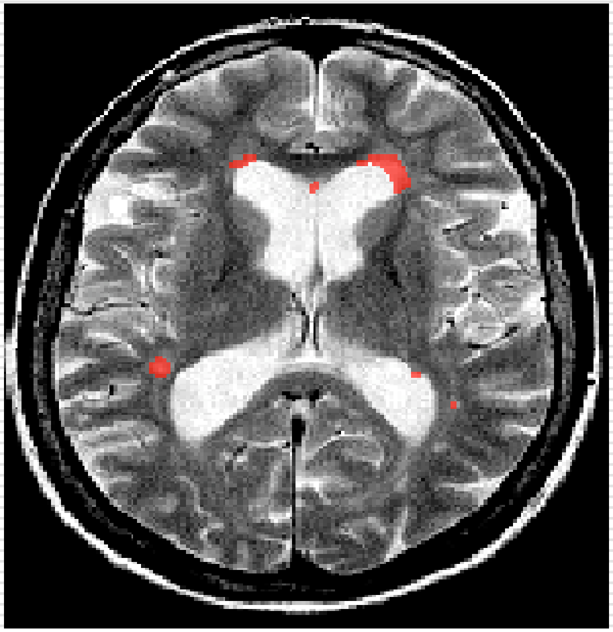
Empirical Results

- Philips scanner multi-spectral data from 25 pre-segmented MRI volumes
  - 15 MRI volumes used for training
  - 10 MRI volumes used for evaluation
- Lesions identified by a consensus of 5 experts forming silver standard for evaluation
- κ-metric for reporting results

Qualitative Results: Sparse lesions

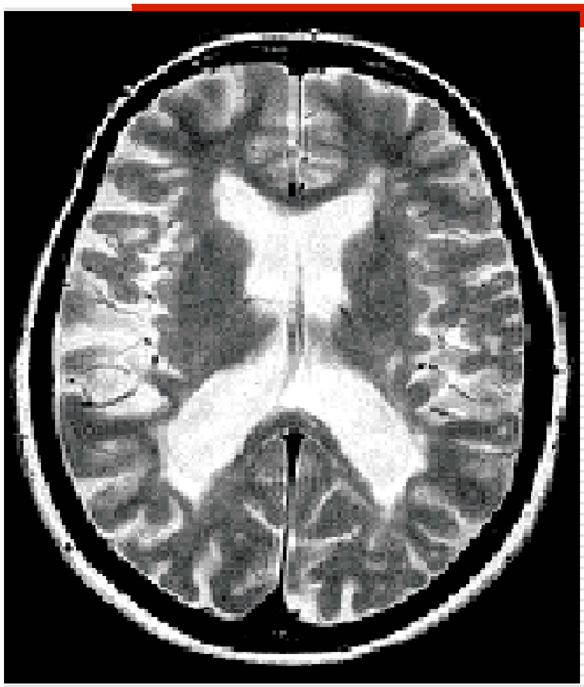
T2w

Expert

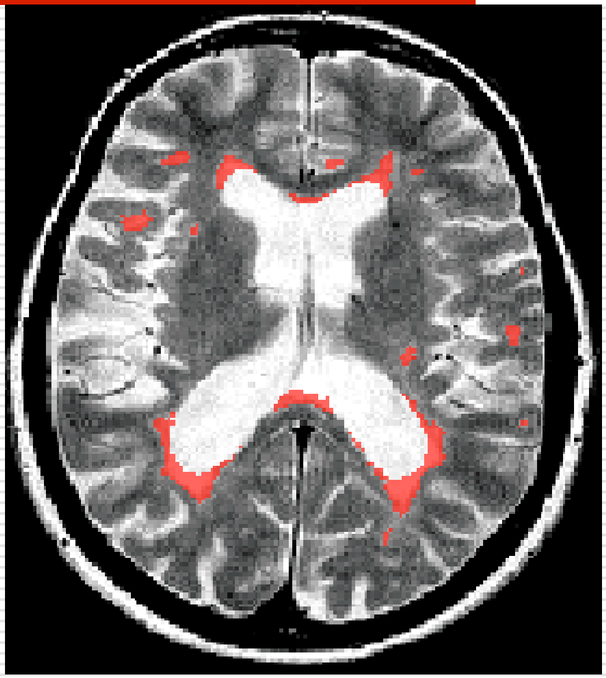


MRF

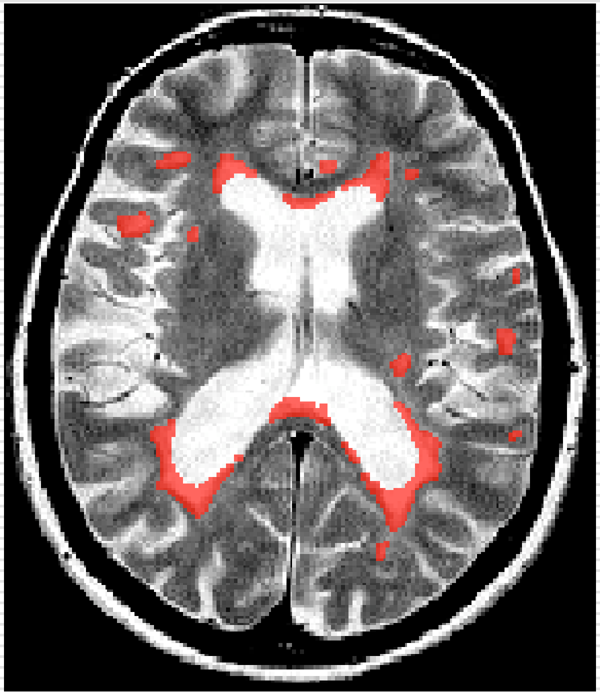
Qualitative Results: Cortical lesions



T2w

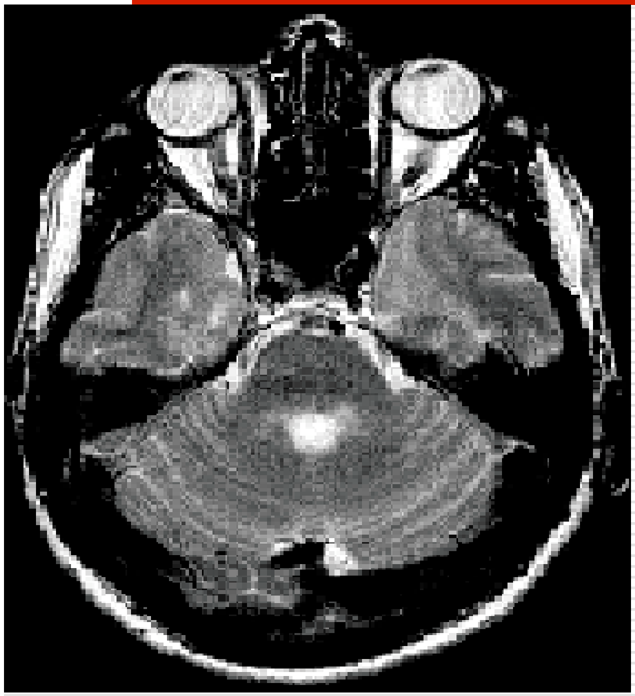


Expert

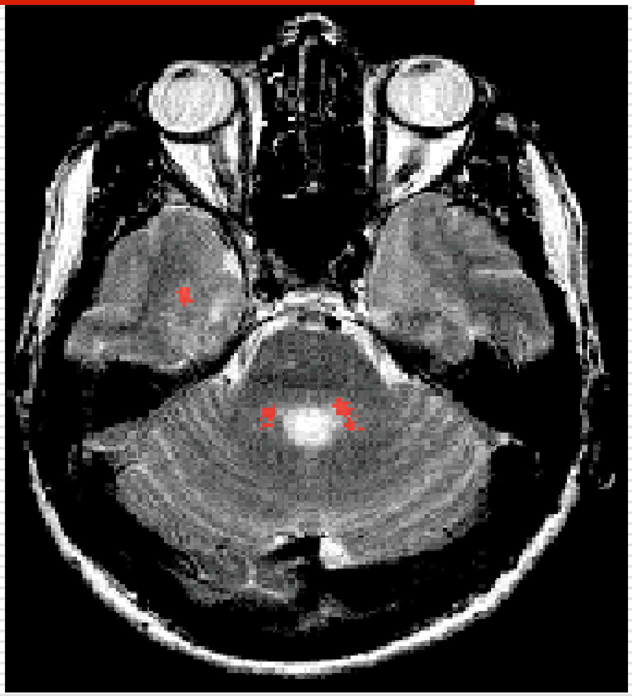


MRF

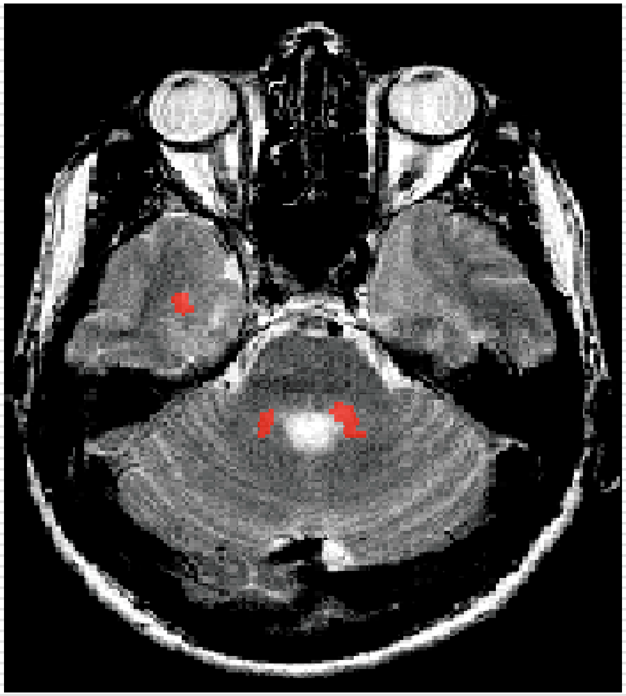
Qualitative Results: Posterior Fossa



T2w

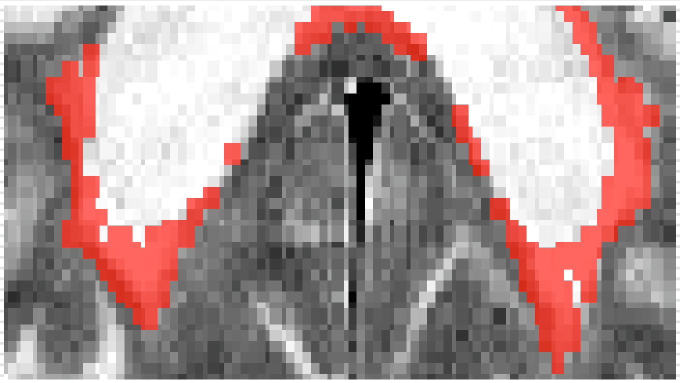


Expert

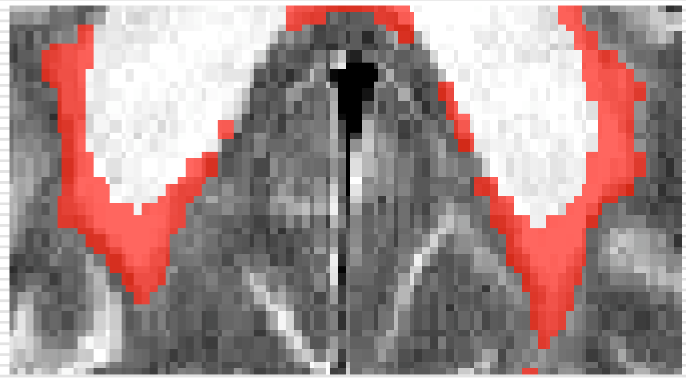


MRF

Smoothing

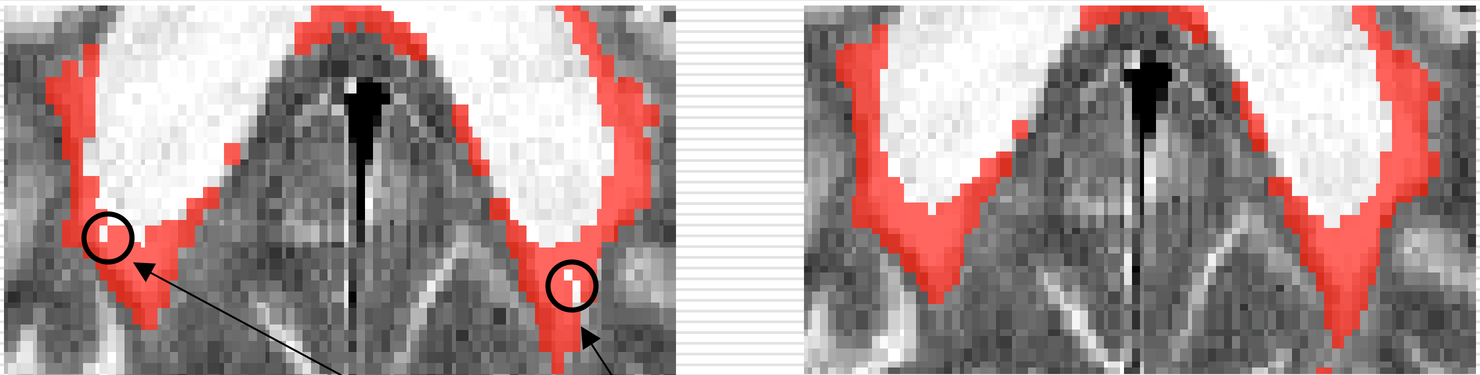


Before



After

Smoothing



Before

After

discontinuities

Quantitative Results

MRF Results (agreement with silver standard)

Patient	1	2	3	4	5	6	7	8	9	10	Mean
κ (PF)	0.61	0.69	0.48	0.56	0.69	0.74	0.73	0.63	0.62	0.68	0.64
κ (no PF)	0.63	0.70	0.50	0.58	0.71	0.74	0.74	0.64	0.66	0.7	0.67

Raters' Agreement

Median κ	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5
Expert 1	-	-	-	-	-
Expert 2	0.68	-	-	-	-
Expert 3	0.57	0.64	-	-	-
Expert 4	0.56	0.62	0.54	-	-
Expert 5	0.65	0.76	0.67	0.60	-

False Positive and False Negative Rates

Patient	False +ve Rate	False -ves Rate
1	0.003	0.13
2	0.002	0.06
3	0.001	0.05
4	0.004	0.06
5	0.003	0.09
6	0.0004	0.19
7	0.0006	0.11
8	0.0003	0.14
9	0.001	0.12
10	0.005	0.06
Mean	0.002	0.10

Conclusion and Future Work

- MRF approach gives encouraging results on real MRI lesion segmentation
- Relatively better performance on Posterior Fossa

To Do:

- Loosening the homogenous and isotropic assumption on neighborhood
- Optimizing the framework to incorporate smoothing
- Exploiting the anatomical dependencies of lesion occurrences

Thank You