Segmentation of Cerebrovascular Pathologies in Stroke Patients with Spatial and Shape Priors

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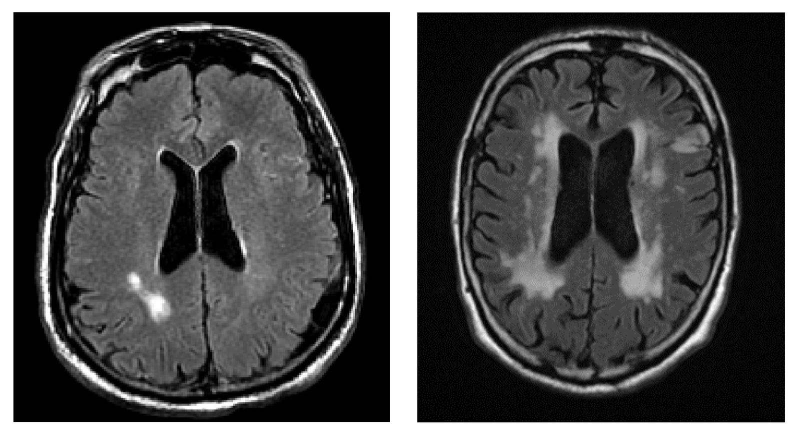
Motivation

Goal: automatically segment and separate small vessel disease (leukoaraiosis) and stroke lesions in T2-FLAIR of stroke patients.

Cerebrovascular Pathologies

- Small vessel disease predictor of stroke outcome
- Pathologies have similar intensities in T2-FLAIR
- Stroke has no consistent shape or location pattern
- Clinicians use spatial patterns in small vessel disease to differentiate from stroke lesions



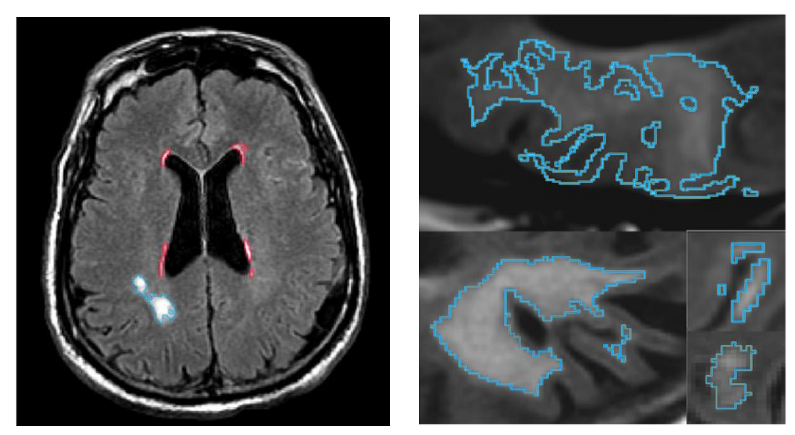
Stroke patients with pathologies

Current Methods

- Segment hyperintensities via intensity thresholds
- Shape models used for other segmentation tasks

Our Method

- Model combines intensity and spatial patterns
- Inference to segment and differentiate pathologies



small vessel disease, stroke lesions

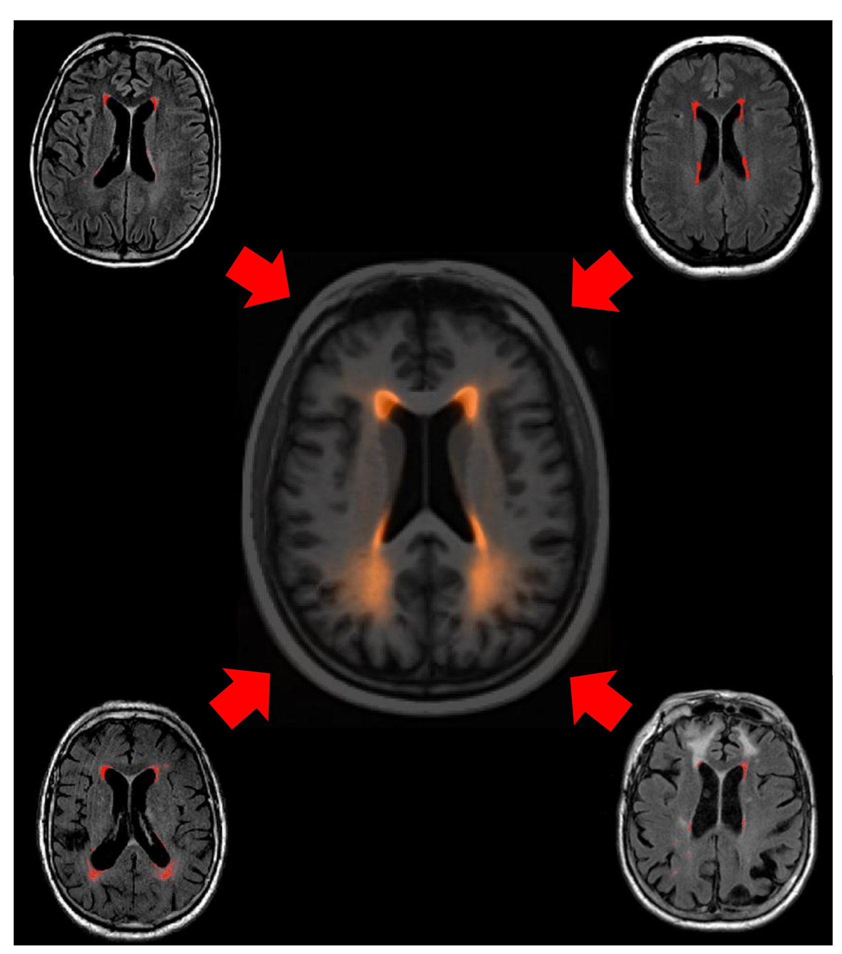
Spatial Model - Small Vessel Disease

Common Space

- Register training subjects
- Maps of small vessel disease overlap (obtained manually)

Spatial Model M

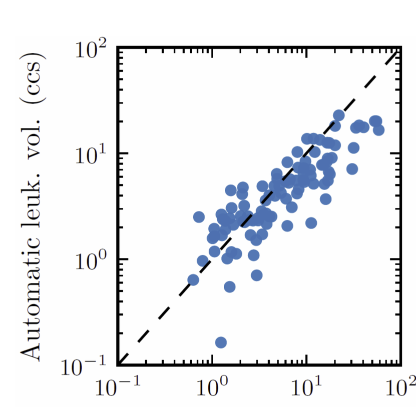
- PCA on maps of small vessel disease
- Components M_k capture co-variation e.g. bilateral periventricular symmetry
- Properties match those used by clinicians
- Can project estimated small vessel disease onto model

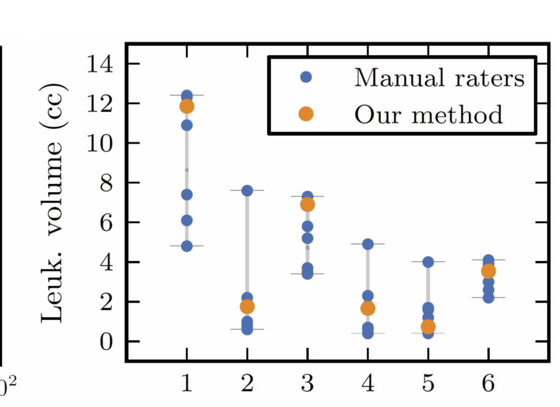


Segmentation Results

Manual vs Automatic segmentation

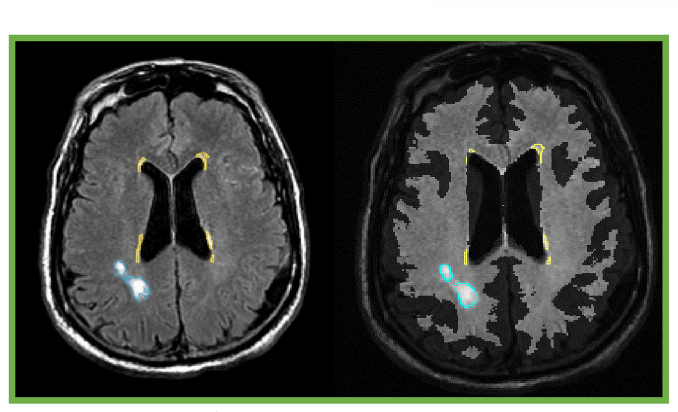
- Good agreement of lesion outlines
- Volume agreement (100 subj) $r = 0.82$
- Volume agreement across manual raters



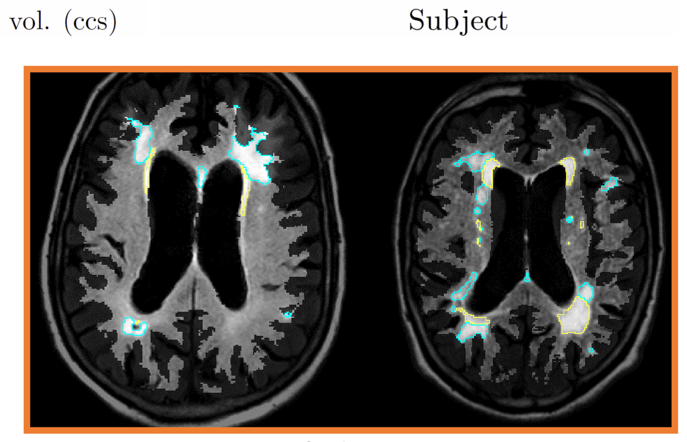


Failure Cases

- Bad registration
- Large extent of small vessel disease volumes



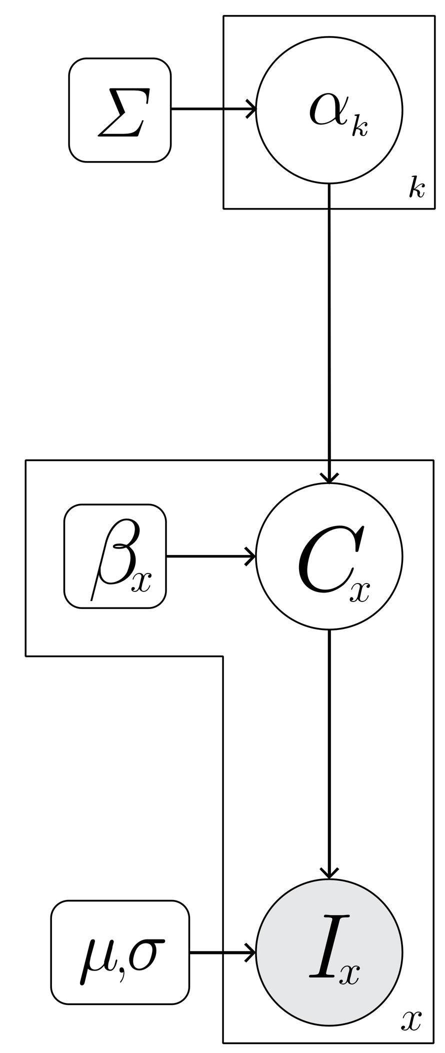
manual automatic



failure cases

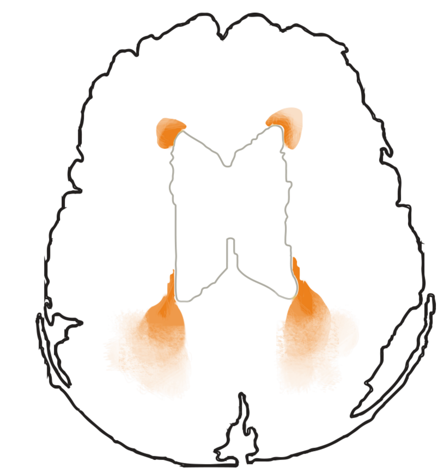
Generative Model for T2-FLAIR

We model three tissue classes: small vessel disease, stroke, and healthy



Small Vessel Disease Spatial Prior $M(\alpha)$

- Generate parameters α_k
  $P(\alpha) = \mathcal{N}(\alpha; 0, \Sigma)$
  $M(\alpha) = \bar{M} + \sum_k \alpha_k M_k$

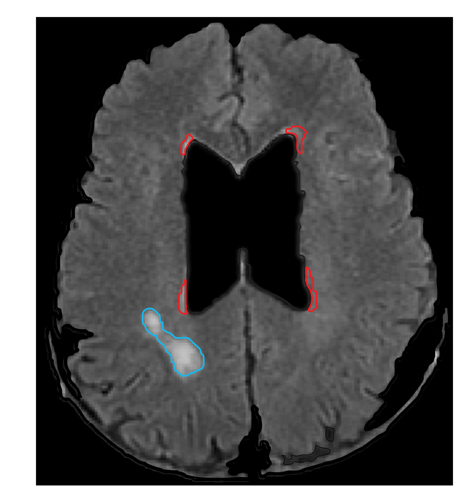


Tissue Priors for Class C_x

- $P(C_x|\alpha;\beta) = \begin{cases} M_x(\alpha) & \text{small vessel disease} \\ (1-M_x(\alpha))\beta_x & \text{stroke} \\ (1-M_x(\alpha))(1-\beta_x) & \text{healthy} \end{cases}$
- Add MRF for spatial contiguity

Intensity Observations

- Generated independently from Gaussian
  $P(I_x|C_x;\mu,\sigma) = \prod_c \mathcal{N}(I_x;\mu_c,\sigma_c)^{C_x=c}$



Joint Probability

$P(C, I, \alpha; \mu, \sigma, \beta) = P(I|C;\mu,\sigma)P(C|\alpha;\beta)P(\alpha)$

Inference & Segmentation

Segmentation

- MAP estimate via Variational EM inference
  $\hat{C} = \text{argmax}_C P(C|I,\alpha;\mu,\sigma,\beta)$

Initialize

- Hyperintense voxels: small vessel disease, stroke

E-Step Update

- Estimate small vessel disease spatial prior $M(\alpha)$ via regularized projection of small vessel disease

M-Step Updates

Small vessel disease and stroke probability maps

- Estimate for class statistics μ_c, σ_c
  Include healthy tissue heterogeneity model
- Update tissue prior based on previous MAP estimates and $M(\alpha)$
- Update posterior $\hat{C}_x$ using new class statistics, tissue prior, and neighbor agreement

Convergence leads to delineation of small vessel disease and stroke lesions simultaneously