Consensus approach to neuroimaging: MAPAWAMO analysis with Lyngby

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OVERVIEW

- Lyngby
- Molgedey-Schuster ICA
- Consensus modeling

LYNGBY

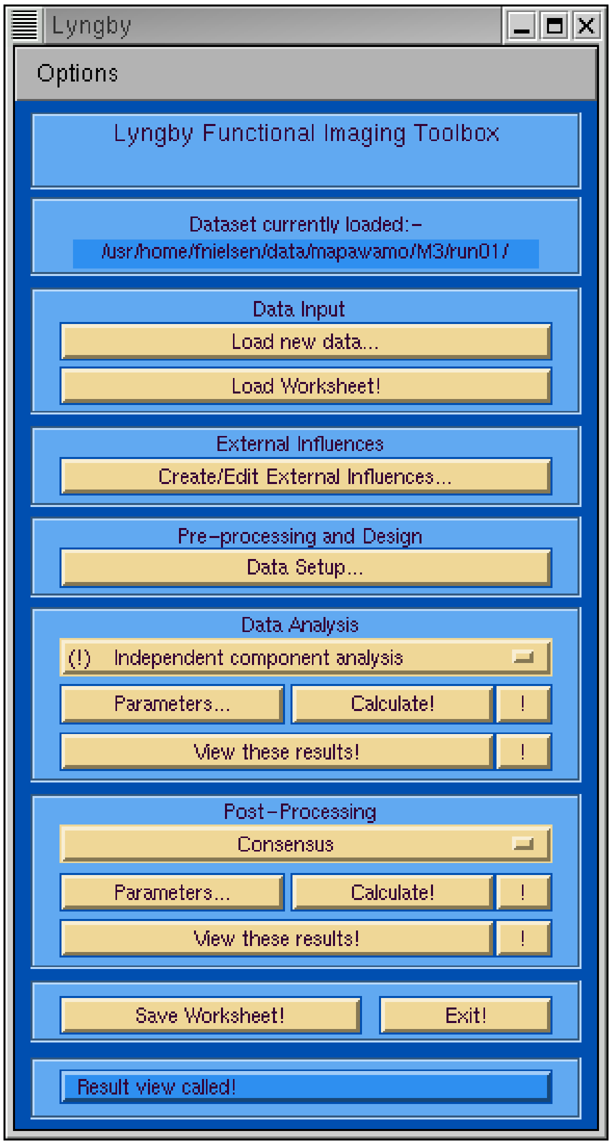

Figure 1: Lyngby main window.

- Modeling toolbox for functional neuroimaging
- http://hendrix.imm.dtu.dk/software/lyngby/

LYNGBY

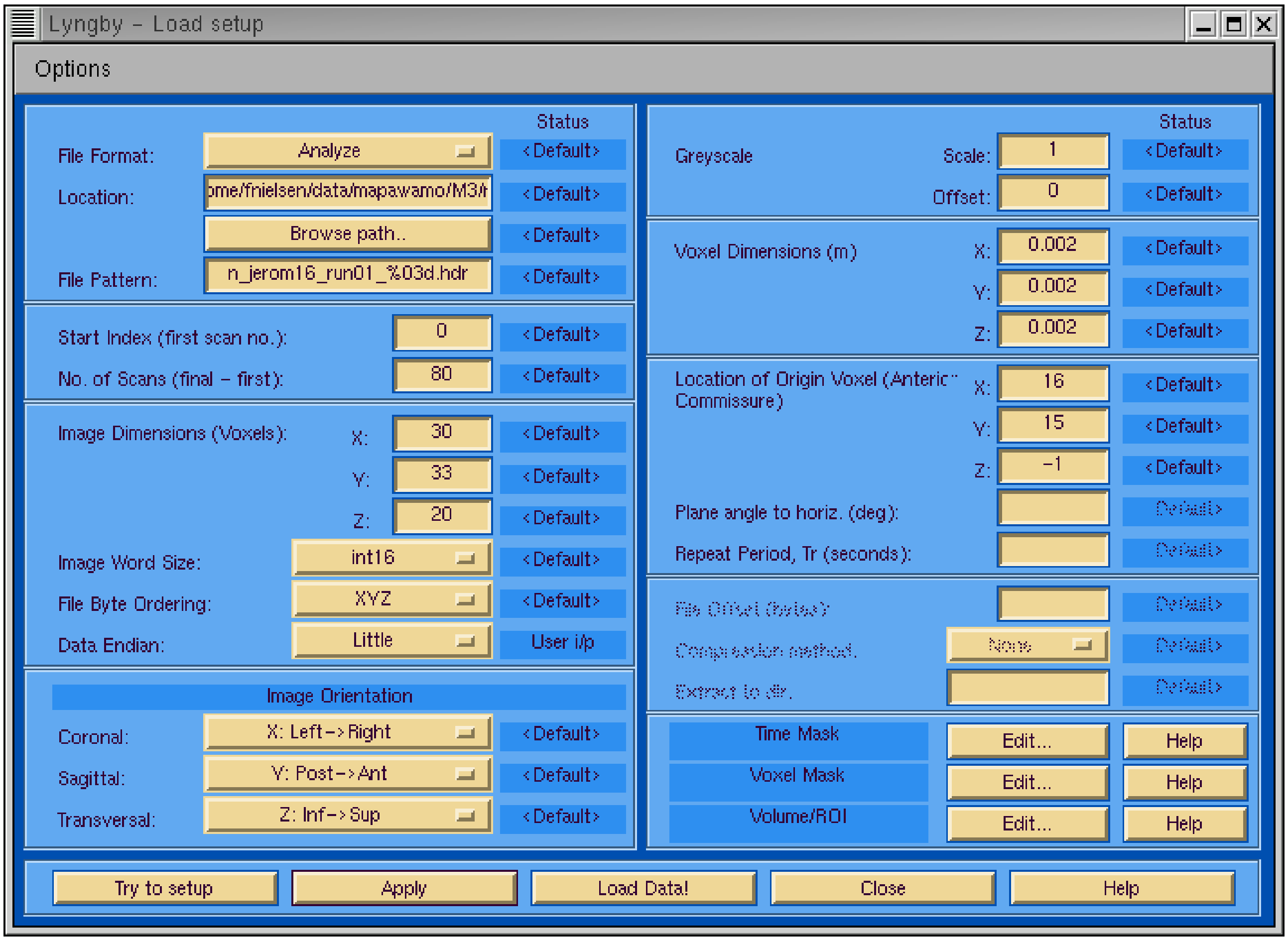

Figure 2: Lyngby result windows with the result from a K-means clustering analysis.

- Reads and writes with — among others — the SPM ANALYZE file format, e.g., from SPM preprocessing (`sn_*.img`).

LYNGBY

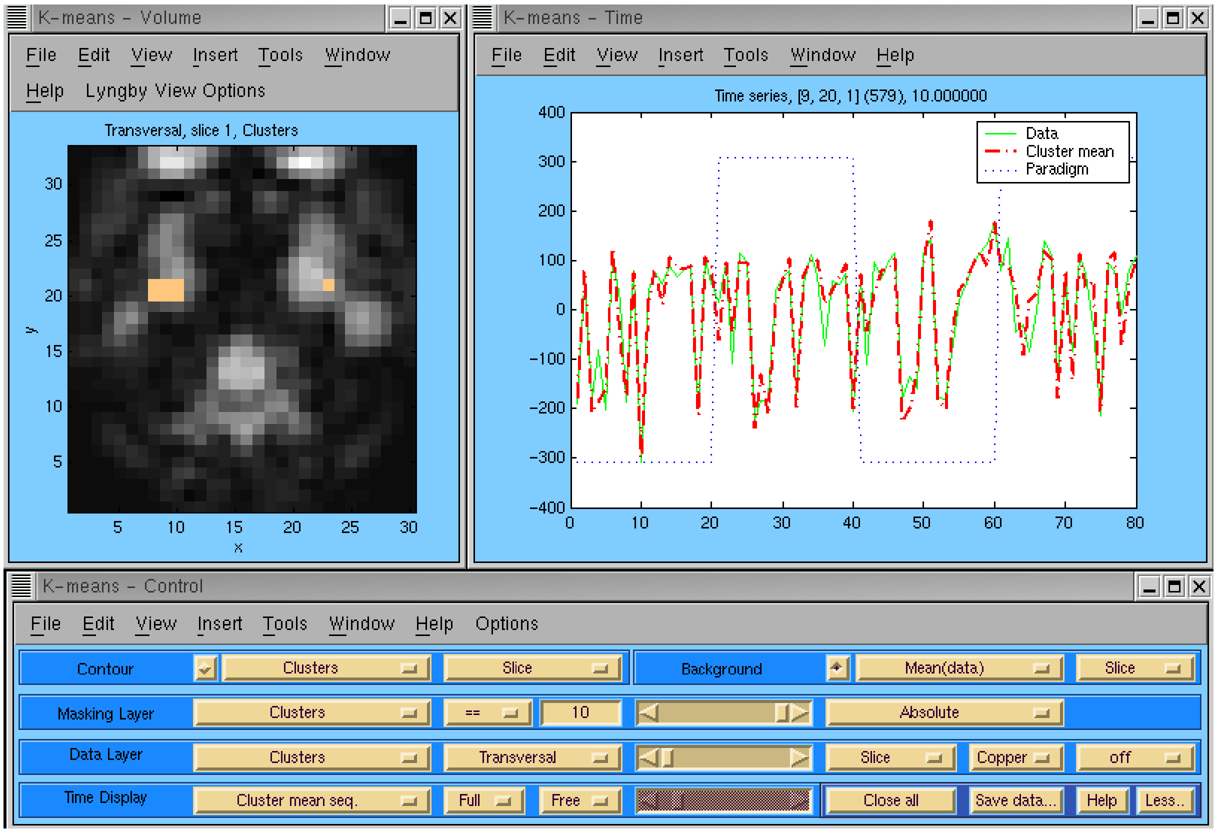

Figure 3: Lyngby result window.

- Use memory, rather than files.
  - Only small data sets are possible. Restrict to a few slices, resample to $2 \times 2 \times 2$mm or use a small number of scans.
  - Quick access to data matrix, e.g., easy to see and save time-series for individual voxels or to "plug into".
- No Talairach space assumptions in visualizations: Will render a monkey brain in its own space.

MOLGEDEY-SCHUSTER ICA

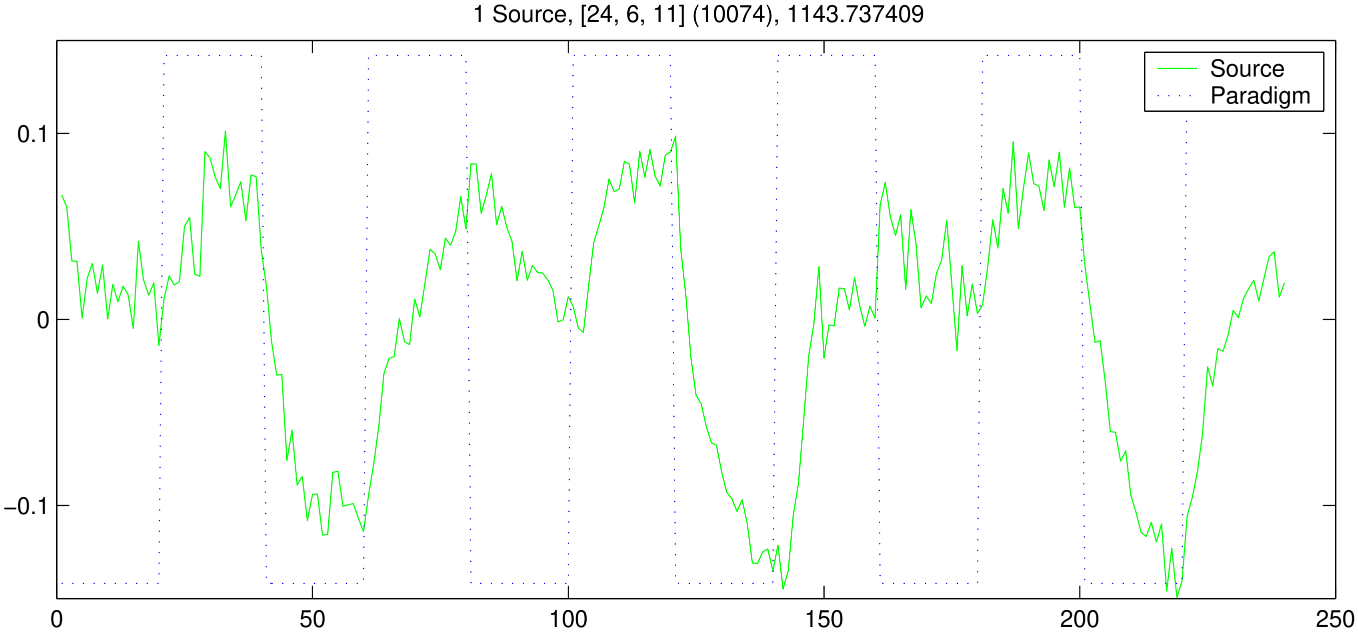

Figure 4: Plot from Lyngby of the first source from a MS ICA.

- Molgedey-Schuster ICA time-delay decorrelation (Molgedey and Schuster 1994).

  Consider the autoregression from 0 to τ

$$\mathbf{X}_\tau = \mathbf{X}\mathbf{W} + \mathbf{U}. \tag{1}$$

$$\hat{\mathbf{W}} = \left[\mathbf{X}^\mathsf{T}\mathbf{X}\right]^{-1}\mathbf{X}^\mathsf{T}\mathbf{X}_\tau. \tag{2}$$

  With $\mathbf{X} = \mathbf{Z}\mathbf{A}$ and independent sources assumption $\mathbf{Z}^\mathsf{T}\mathbf{Z} = \mathbf{\Lambda}$ the mixing matrix $\mathbf{A}$ is found as

$$\text{leig}[\hat{\mathbf{W}}] = \mathbf{A}^{-1}\mathbf{L}\mathbf{A}. \tag{3}$$

- Model for singular data (Hansen and Larsen 1998)

MOLGEDEY-SCHUSTER ICA

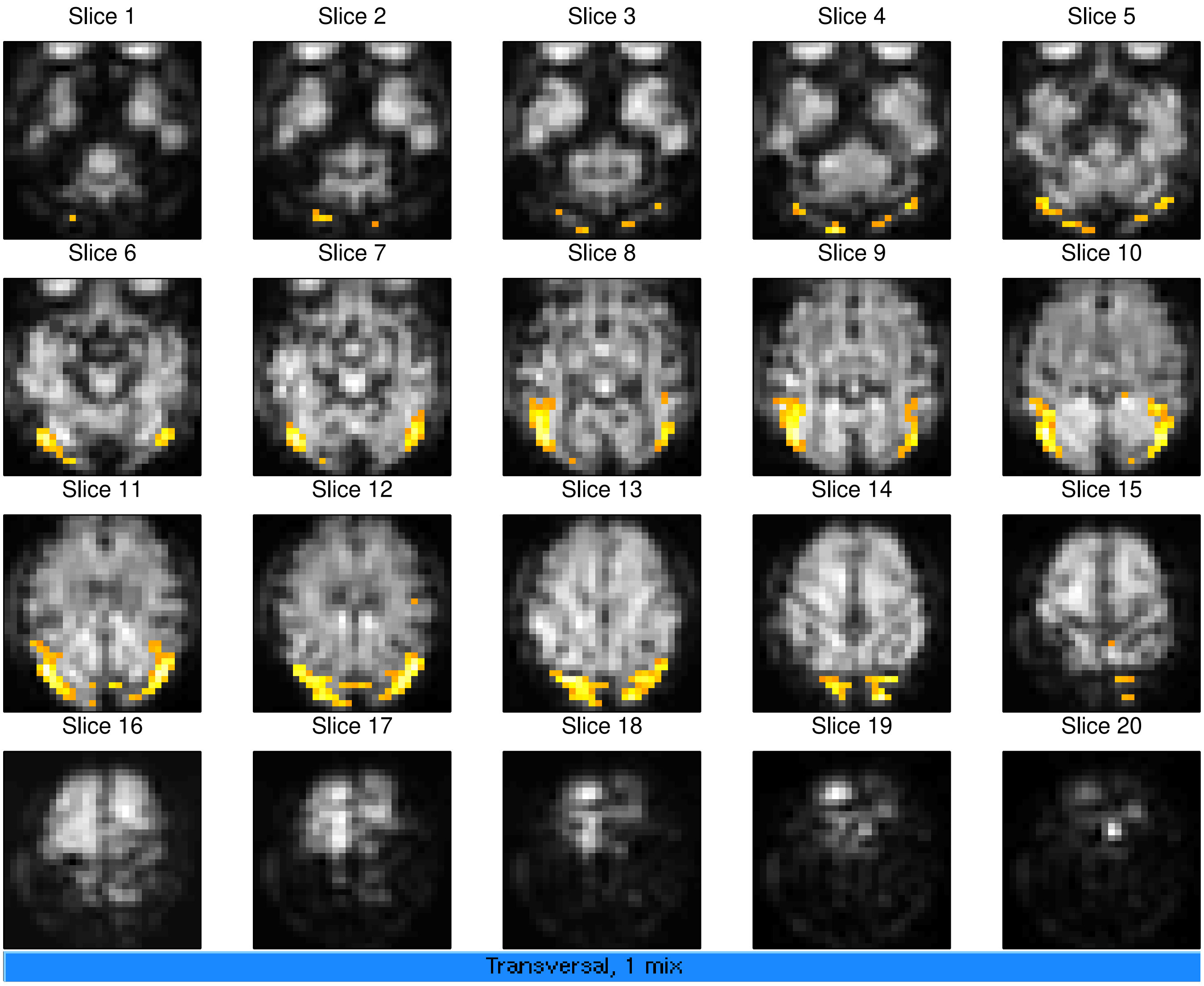

Figure 5: Plot from Lyngby of the mixing matrix of the first ICA component with the mean image of the functional scans. This component correspond

- "Mosaic view" with Lyngby.

CONSENSUS

- Consensus modeling in functional neuroimaging, averaging of histogram equalized models (Hansen, Nielsen, Strother, and Lange 2000).
- Consensus model z' as the average of M histogram equalized summary images s'_m

$$z'(\mathbf{r}) = \frac{1}{M}\sum_{m=1}^{M} s'_m(\mathbf{r}) \tag{4}$$

  where $\mathbf{r}$ is a location (voxel).

- Average error as the mean square from the hypothetical true activation map t'

$$E_{\text{AV}} = \frac{1}{M}\sum_{m=1}^{M}\langle[t'(\mathbf{r}) - s'_m(\mathbf{r})]^2\rangle_{\mathbf{r}} \tag{5}$$

$$E_{\text{AV}} = \underbrace{\langle[t'(\mathbf{r}) - z'(\mathbf{r})]^2\rangle_{\mathbf{r}}}_{\text{Consensus error}} + \underbrace{\frac{1}{M}\sum_{m=1}^{M}\langle[s'_m(\mathbf{r}) - z'(\mathbf{r})]^2\rangle_{\mathbf{r}}}_{\text{Always positive}} \tag{6}$$

CONSENSUS

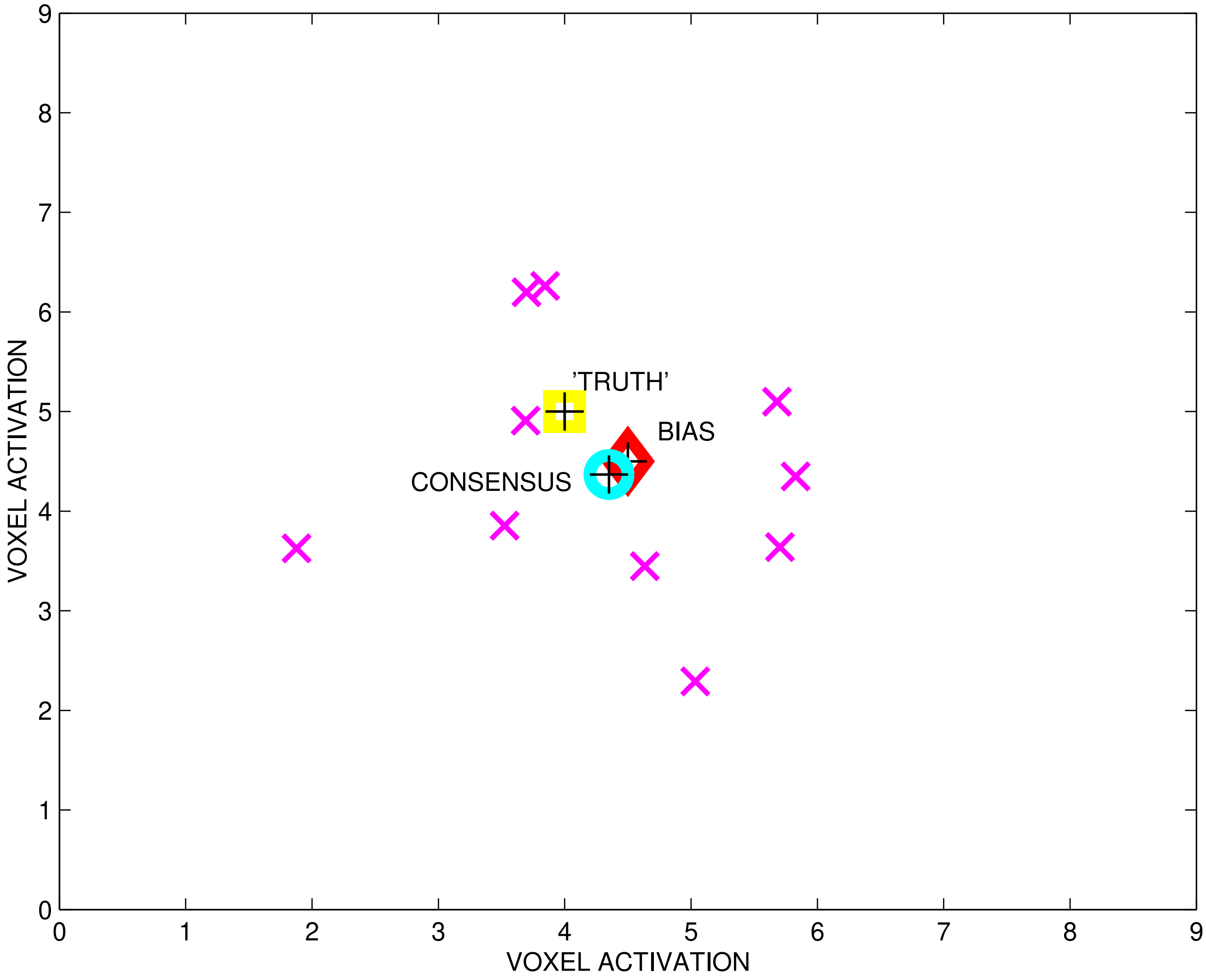

Figure 6: Consensus among biased uncorrelated models.

- Consensus error could potentially be

$$E_{\mathrm{CON}} = \frac{1}{M} E_{\mathrm{AV}} \tag{7}$$

  with unbiased, uncorrelated models.
- Error function should be convex, e.g., Gaussian model errors.

CONSENSUS

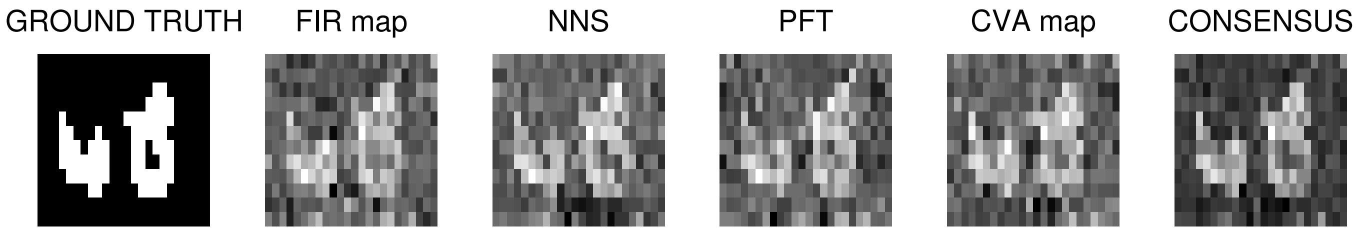

Figure 7: Summary images after histogram equalization for Simple paradigm.

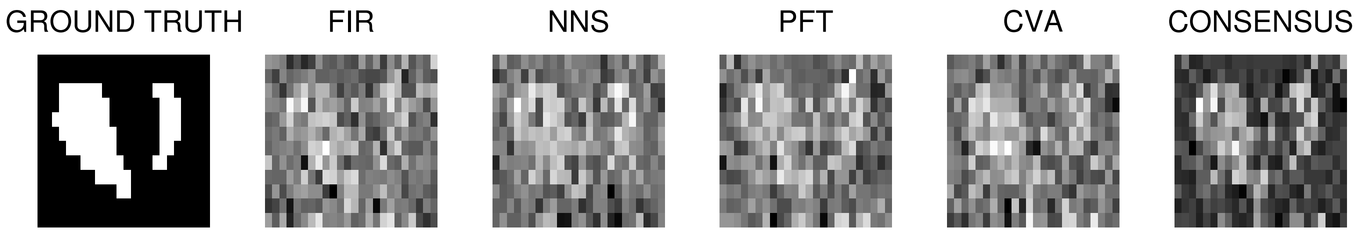

Figure 8: Summary images after histogram equalization for Convolution signal.

- Simulated signals from a model comparison study (Lange, Strother, Anderson, Nielsen, Holmes, Kolenda, Savoy, and Hansen 1999).
  - Small 12×24 patch of null fMRI.
  - Embedded signal: Ground truth known.
- Running different analyses: FIR-filter, artificial neural network saliency map, canonical variate analysis, others …

CONSENSUS

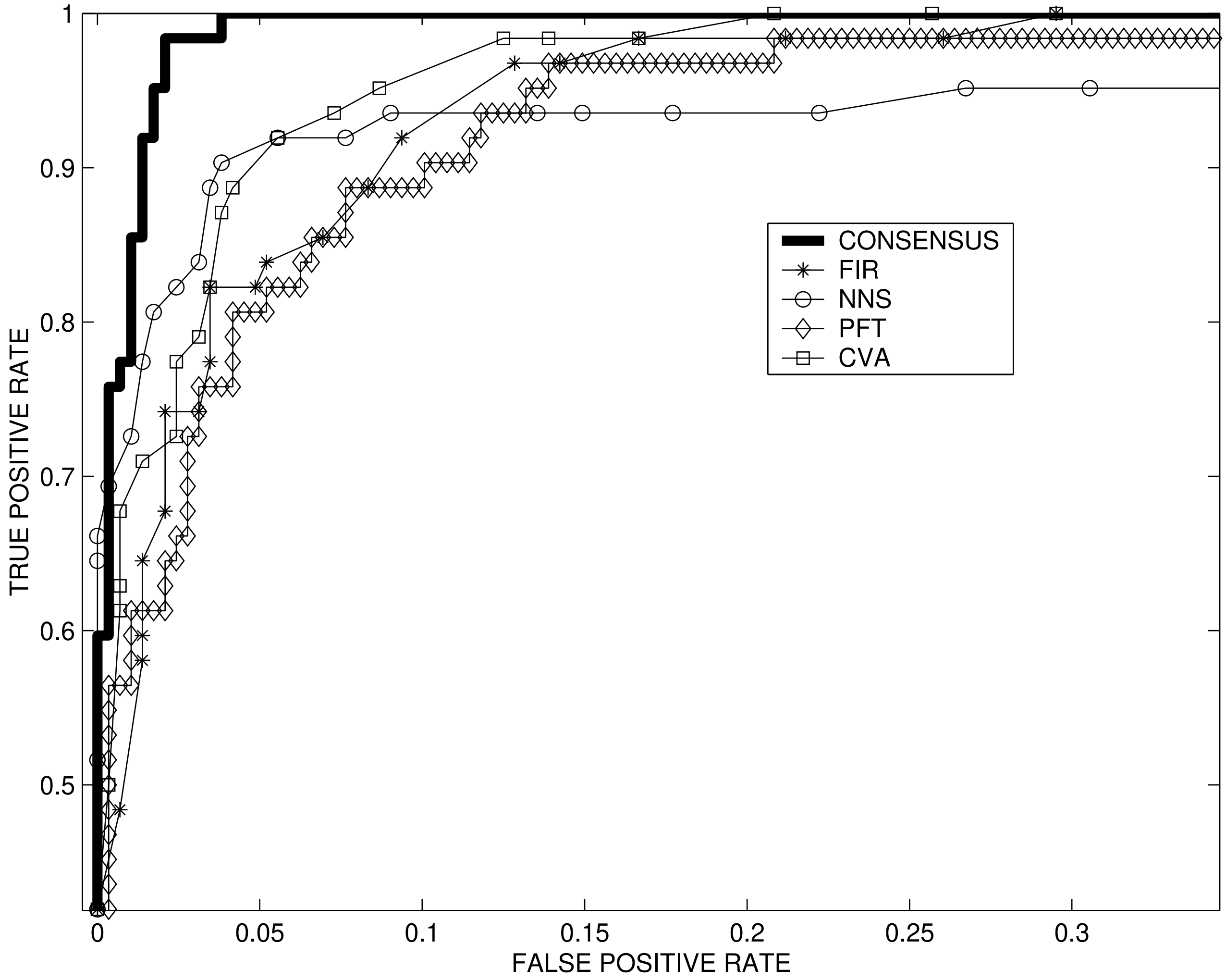

Figure 9: ROC curve for consensus modeling of simulated data set with the Simple signal.

- Consensus model performs better than the average model.
- In this case the consensus model even performs better than any of the other models.

CONSENSUS

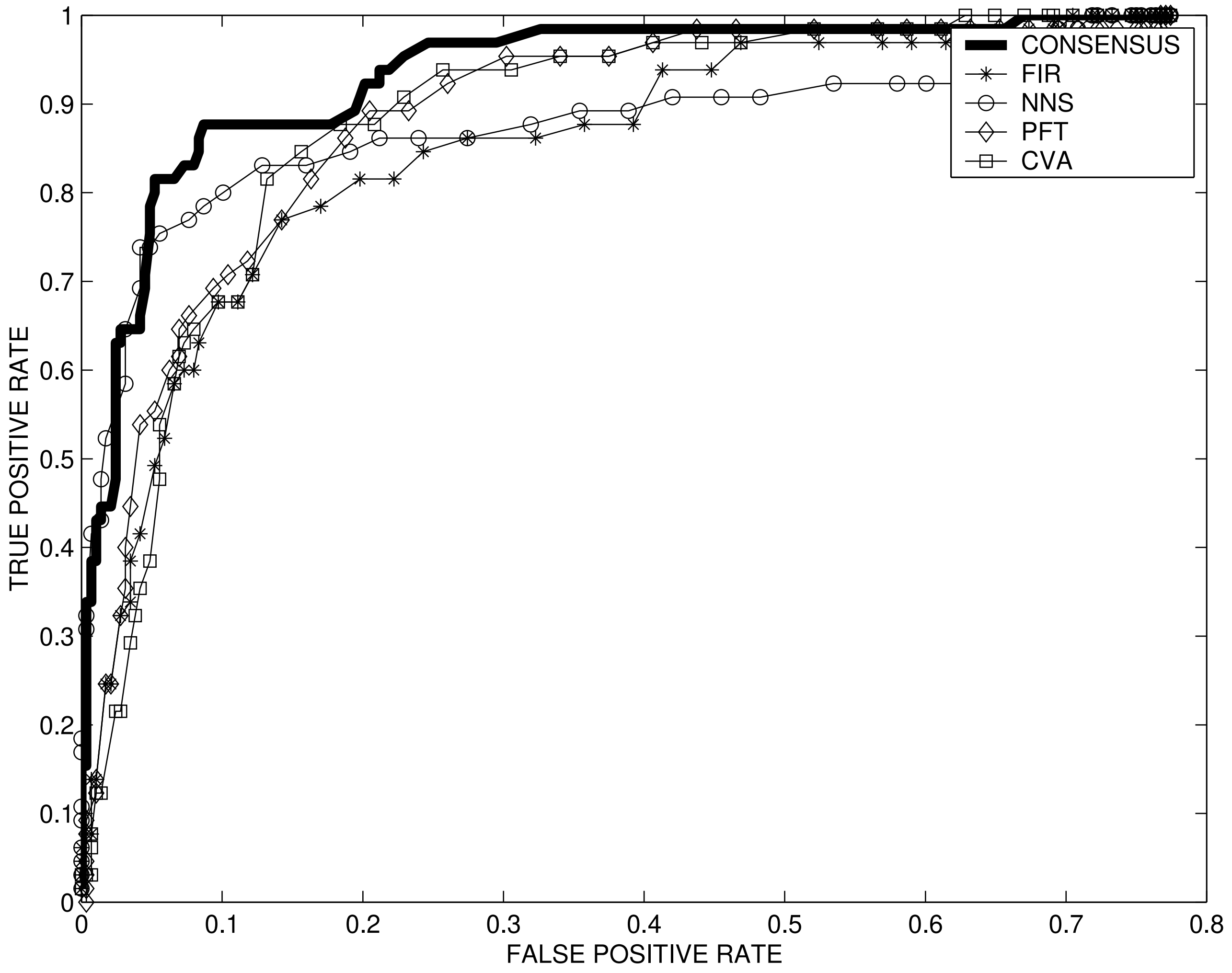

Figure 10: ROC curve for consensus modeling of simulated data set with the Convolution signal.

M3 DATA

- M3 data set (jerom16), — some of the runs used.
- Motion alignment (SPM99).
- Spatial normalization with no nonlinear components and 2mm voxels (SPM99) to EPI MION template provided by Denis Fize: jerom_epi_mion_newTemplate.
- Smoothing with FWHM 1.5mm (SPM99).
- Loaded in Lyngby.

HISTOGRAM EQUALIZATION

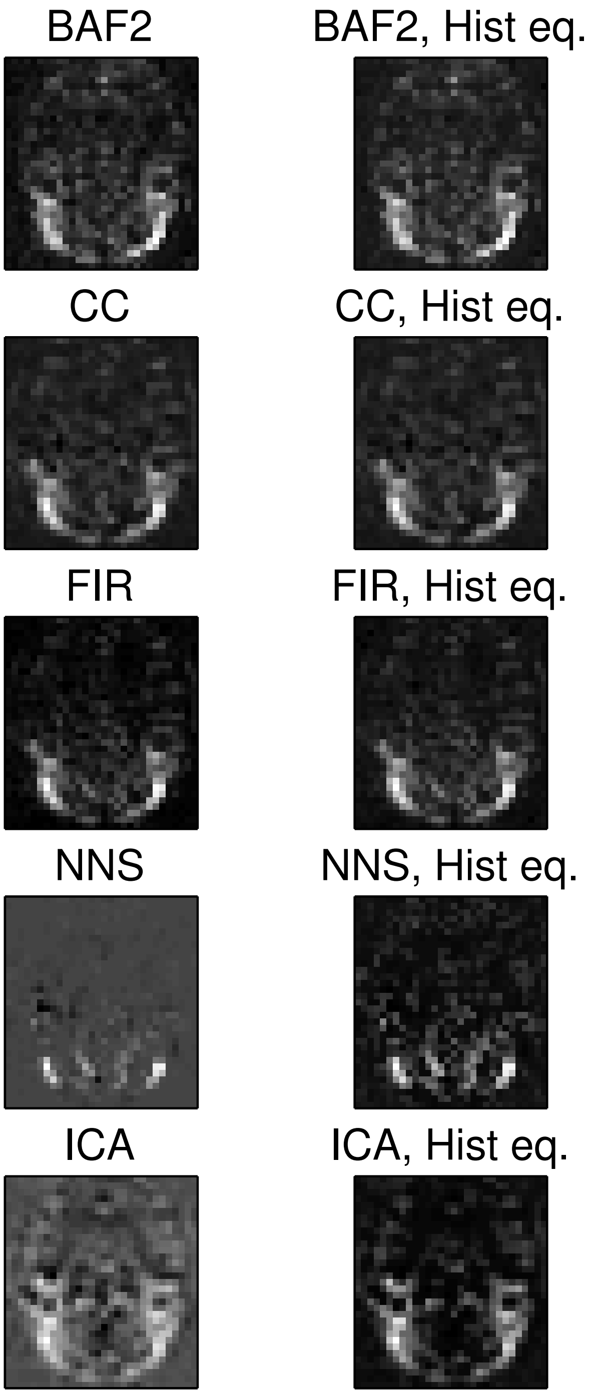

Figure 11: Histogram equalization for M3(jerom) analysis results: Ardekani's F-test with nuisance, cross-correlation, finite impulse response, neural network saliency, independent component analysis (Molgedey-Schuster).

EIGENSPACE OF MODELS

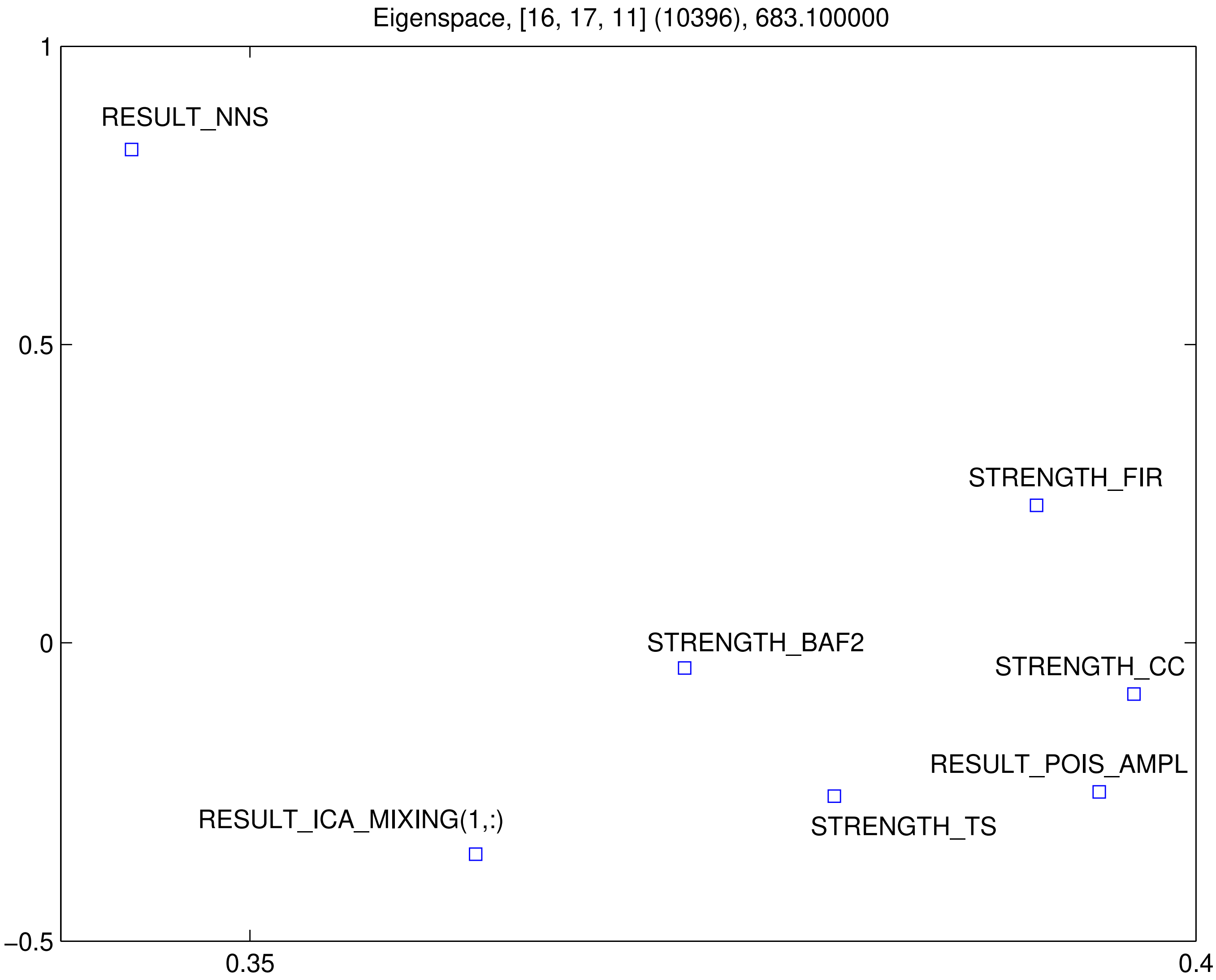

Figure 12: Eigenspace.

- Singular value decomposition of the set of histogram equalized summary images.

M3 CONSENSUS

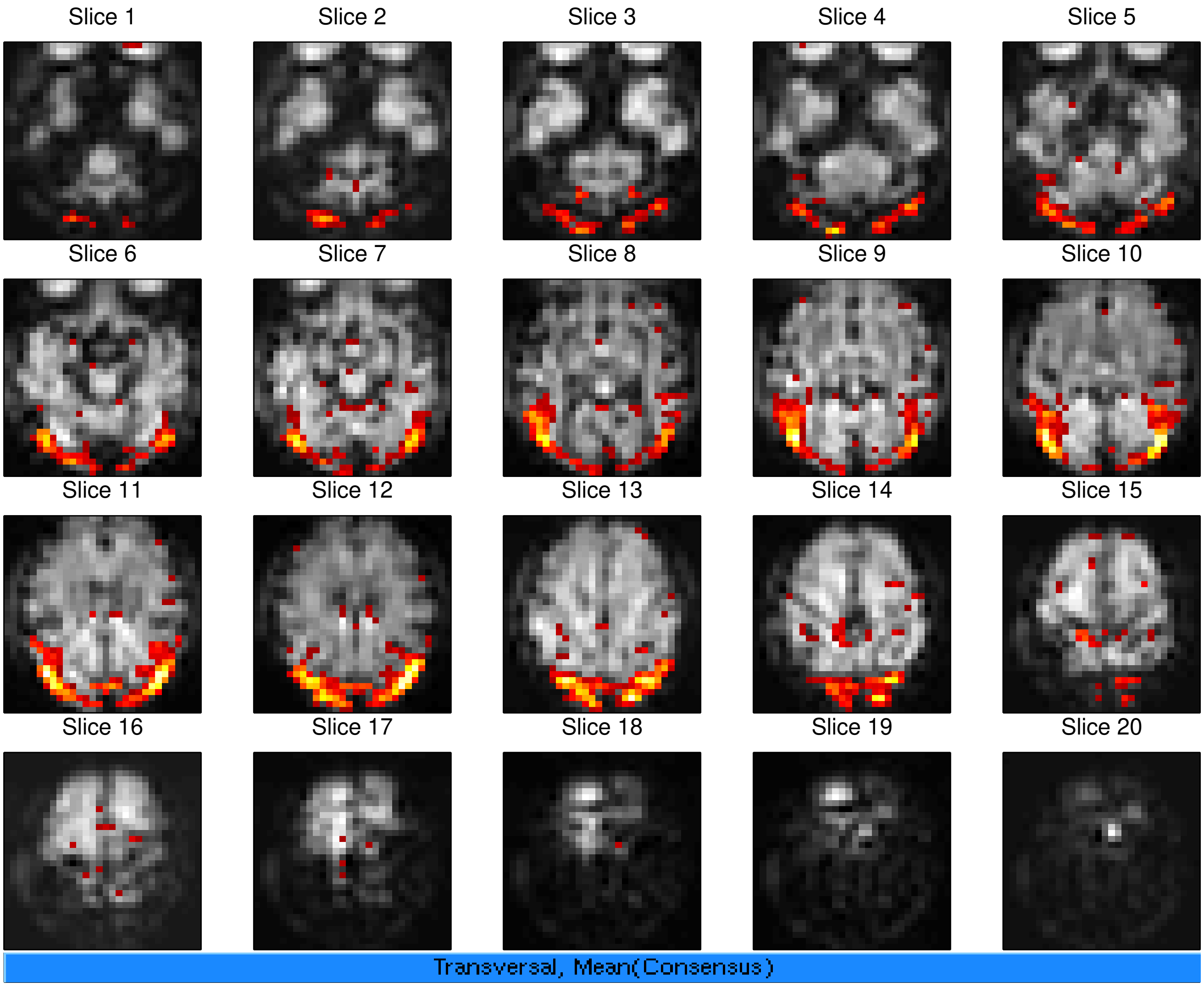

Figure 13: Consensus for 7 analysis of M3(jerom) with 1 run (80 scans).

M3 CONSENSUS 3D VISUALIZATION

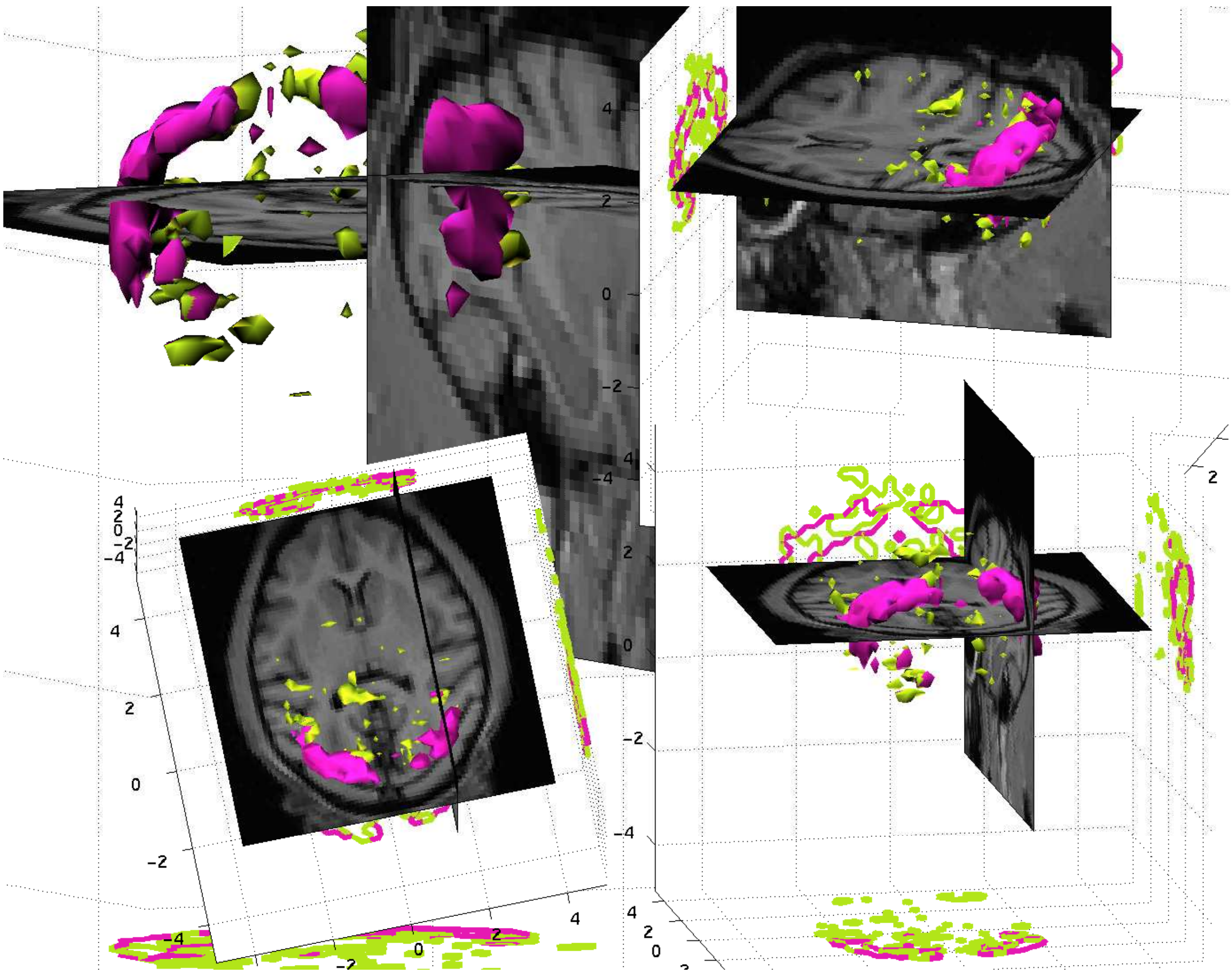

Figure 14: Consensus and divergence for 5 analysis of M3(jerom) rendered in a 3D visualization.

M3 CONSENSUS

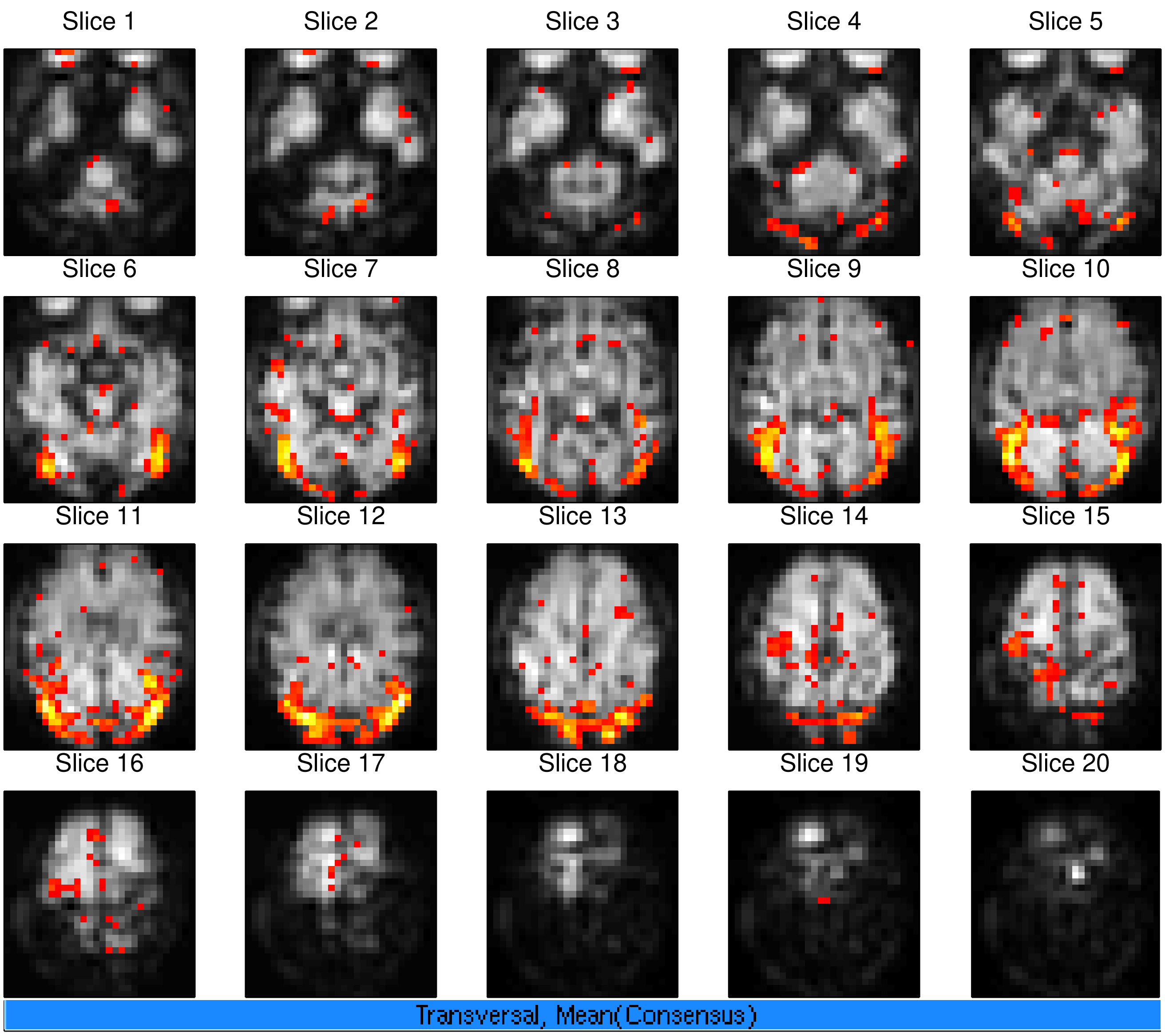

Figure 15: M3(jerom) consensus with excluded "grey" scans.

- Excluding the "Grey" scans and the 6 first for "Stat" and "Mov" to accommodate for the hemodynamic response. 10 runs.

M3 CONSENSUS

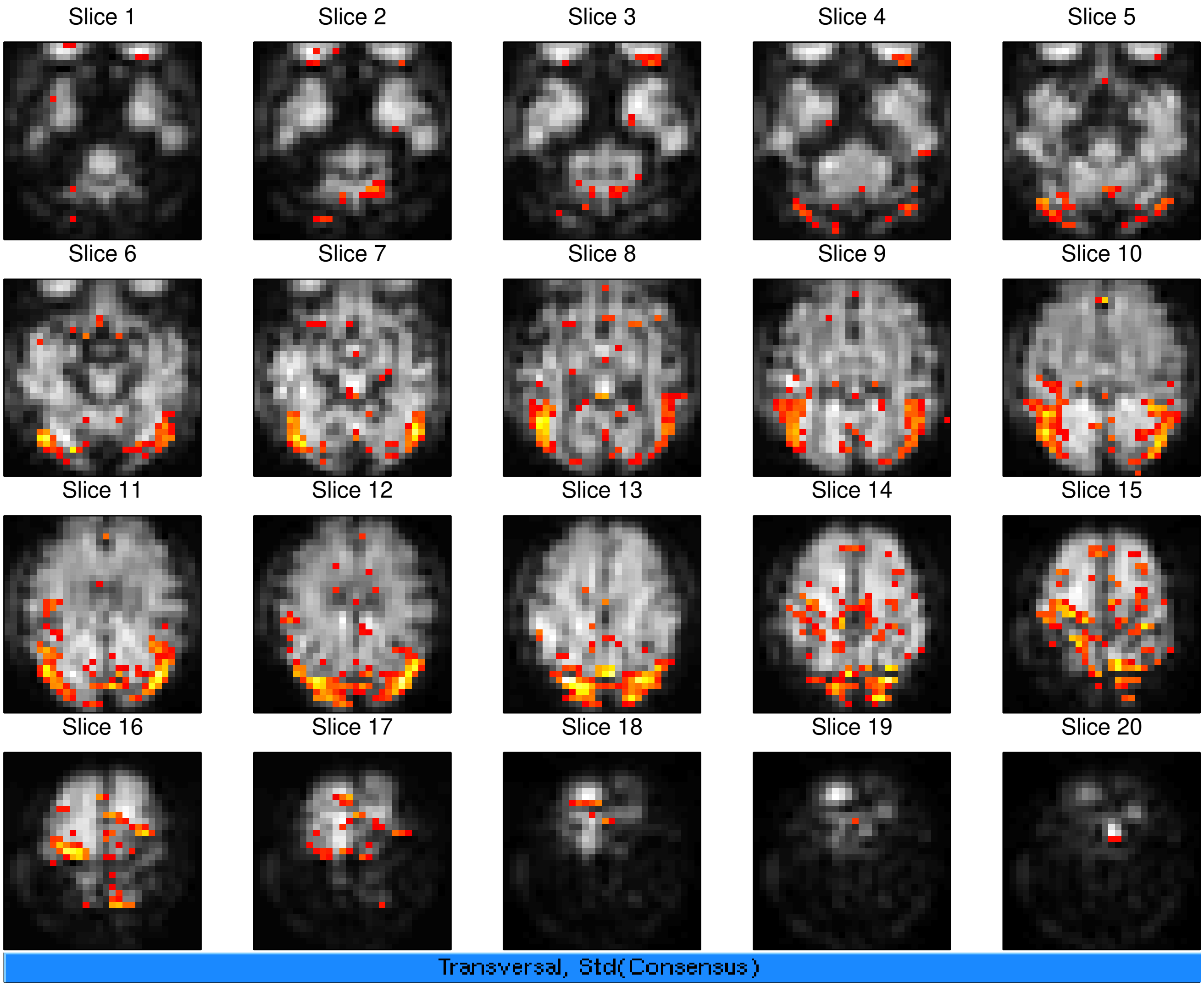

Figure 16: M3(jerom) divergence with excluded "grey" scans.

EIGENSPACE OF MODELS

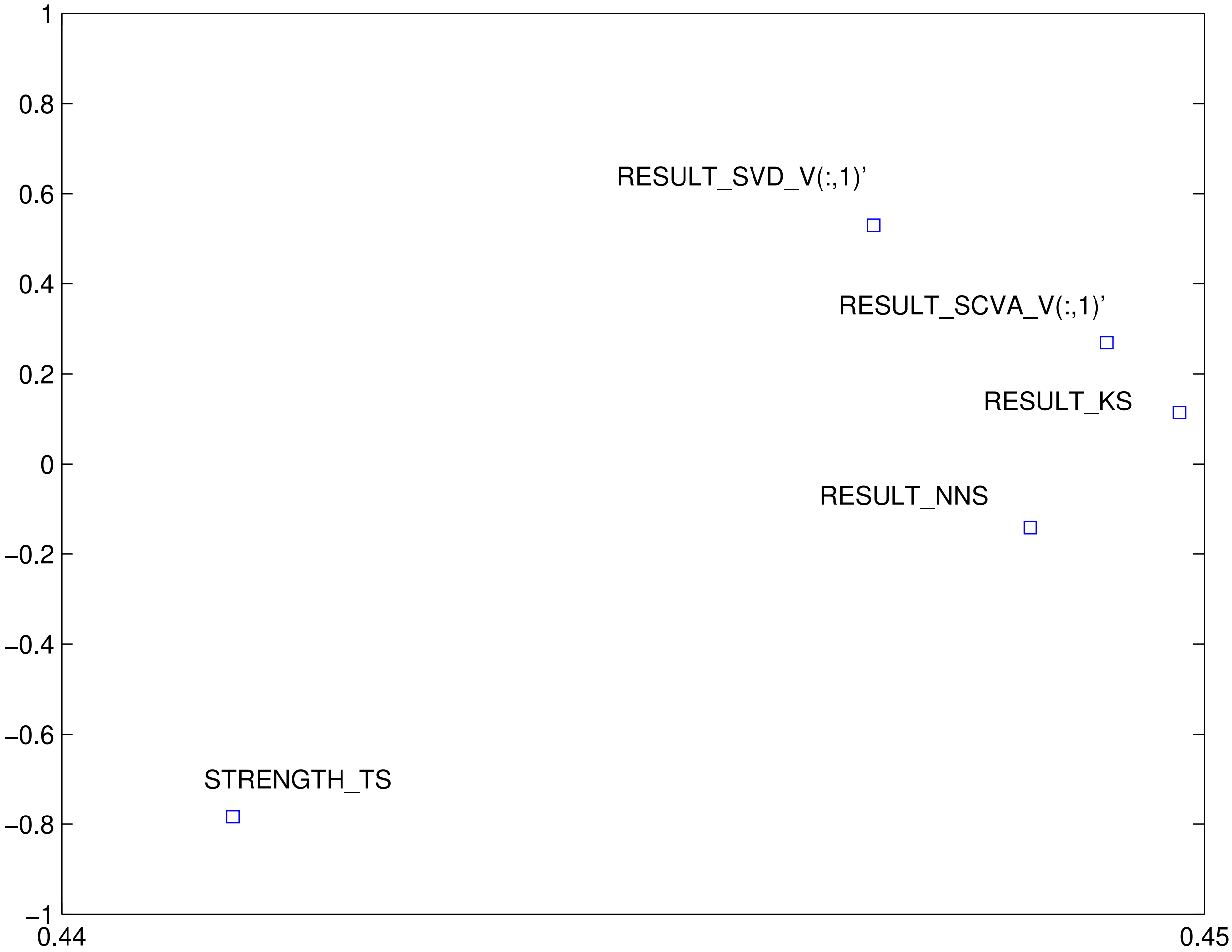

Figure 17: Eigenspace with excluded "grey" scans.

CONSENSUS AND DIVERGENCE

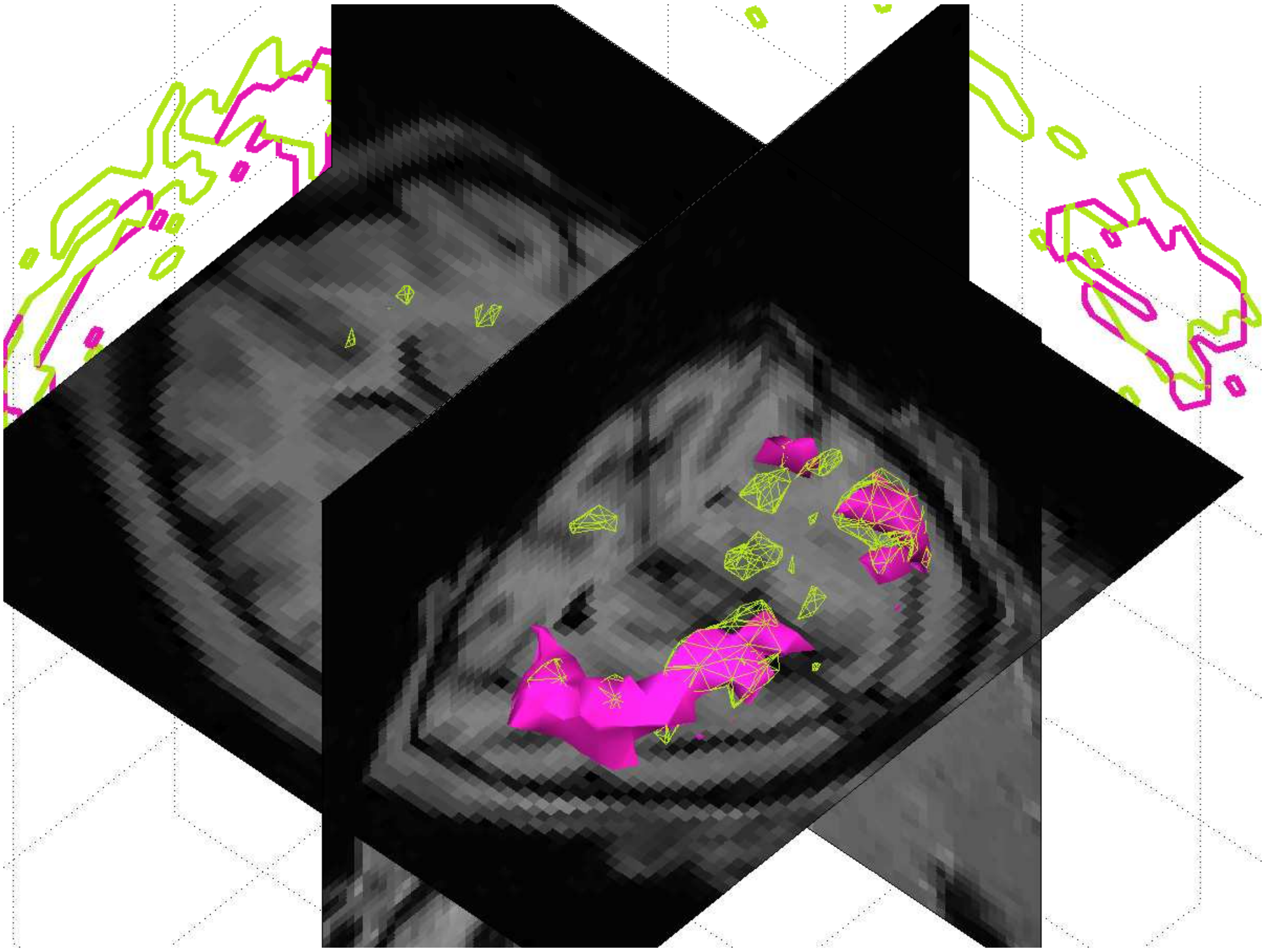

Figure 18: M3(jerom) convegence (magenta) and divergence (green) with excluded "grey" scans.

CONCLUSION

- Consensus models might yield better models than an average individual model.
- M3 MION signal so strong that models agree.
- Models implemented in Lyngby.

MAN AND MONKEY

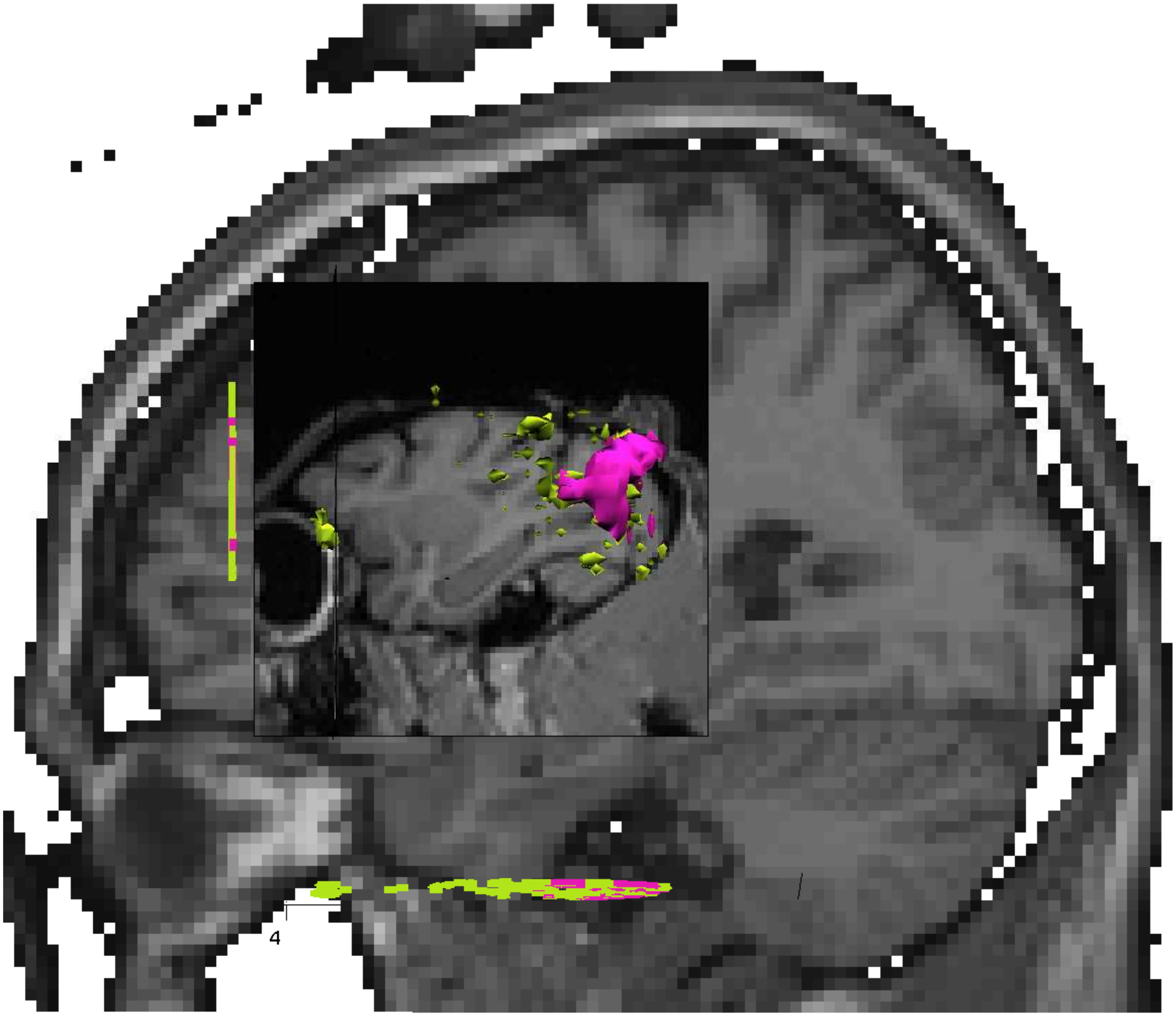

Figure 19: M3(jerom) and "single_subj_T1" from SPM distribution.

REFERENCES

References

Hansen, L. K. and J. Larsen (1998, June). Source separation in short image sequences using delayed correlation. In P. Dalsgaard and S. H. Jensen (Eds.), *Proceedings of NORSIG'98, Vigsø, Denmark*, pp. 253–256.

Hansen, L. K., F. Å. Nielsen, S. C. Strother, and N. Lange (2000, June). Consensus inference in neuroimaging. *NeuroImage 13*(6), 1212–1218.

Lange, N., S. C. Strother, J. R. Anderson, F. Å. Nielsen, A. P. Holmes, T. Kolenda, R. Savoy, and L. K. Hansen (1999, September). Plurality and resemblance in fMRI data analysis. *NeuroImage 10*(3), 282–303.

Molgedey, L. and H. G. Schuster (1994, June). Separation of a mixture of independent signals using time delayed correlations. *Physical Review Letters 72*(23), 3634–3637.

Vanduffel, W., D. Fize, J. B. Mandeville, K. Nelissen, P. V. Hecke, B. R. Rosen, R. B. H. Tootell, and G. Orban (2001, November). Visual motion processing investigated using contrast agent-enhanced fMRI in awake behaving monkey. *Neuron 32*(4), 565–577.