Non-negative partial least squares for meta-analytic parcellation of the human brain

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Parcellation of the human brain

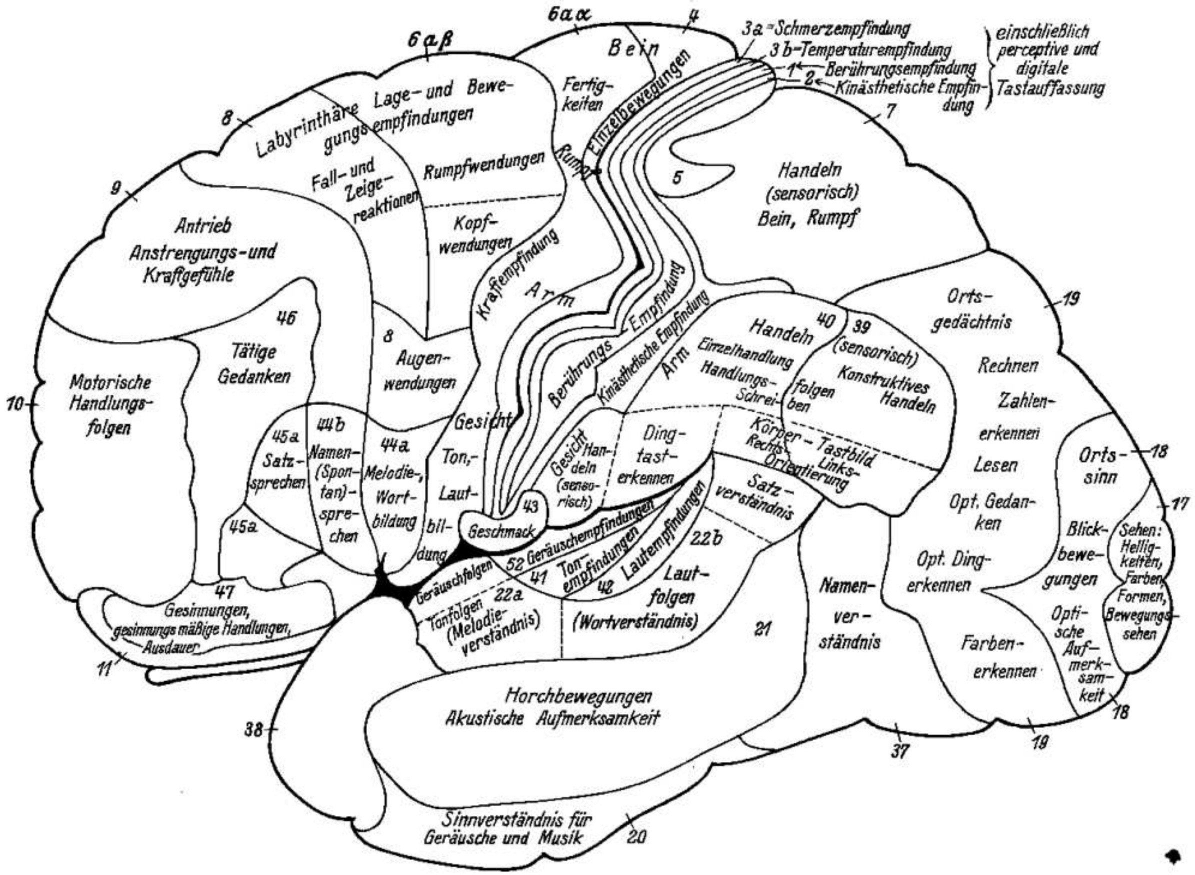


Figure 1: Parcellation of the dorsal surface of the human brain from (Kleist, 1934, figure 429).

"Functional atlas"

Complete atlas for the entire human brain based on brain lesion and their associated change of behavior (Kleist, 1934).

"Manual" analysis of brain lesions.

Computer-based meta-analysis

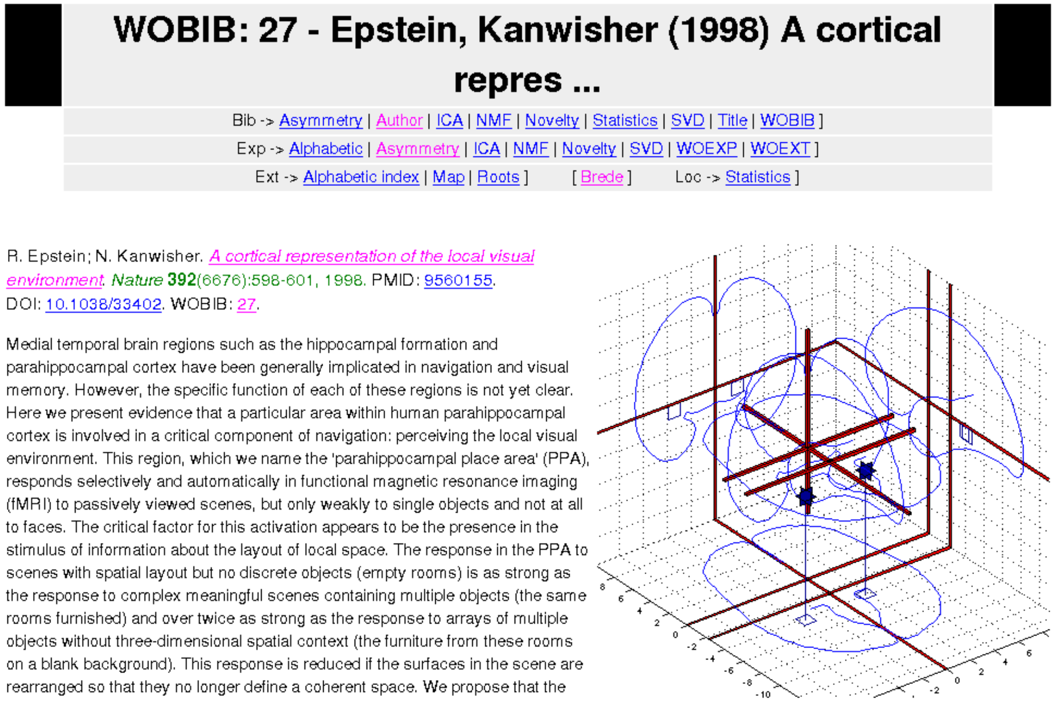
Is it now possible to automatically construct a functional atlas?

Here:

Brede Database + Multivariate analysis → Functional Parcellation

Extension of some of our previous efforts to data mine for brain-function associations (Nielsen et al., 2004).

Brede Database



WOBIB: 27 - Epstein, Kanwisher (1998) A cortical repres ...

Bib -> Asymmetry | Author | ICA | NMF | Novelty | Statistics | SVD | Title | WOBIB]
Exp -> Alphabetic | Asymmetry | ICA | NMF | Novelty | SVD | WOEXP | WOEXT]
Ext -> Alphabetic index | Map | Roots] [Brede] Loc -> Statistics]

R. Epstein; N. Kanwisher. *A cortical representation of the local visual environment*. *Nature* **392**(6676):598-601, 1998. PMID: 9560155. DOI: 10.1038/33402. WOBIB: 27.

Medial temporal brain regions such as the hippocampal formation and parahippocampal cortex have been generally implicated in navigation and visual memory. However, the specific function of each of these regions is not yet clear. Here we present evidence that a particular area within human parahippocampal cortex is involved in a critical component of navigation: perceiving the local visual environment. This region, which we name the 'parahippocampal place area' (PPA), responds selectively and automatically in functional magnetic resonance imaging (fMRI) to passively viewed scenes, but only weakly to single objects and not at all to faces. The critical factor for this activation appears to be the presence in the stimulus of information about the layout of local space. The response in the PPA to scenes with spatial layout but no discrete objects (empty rooms) is as strong as the response to complex meaningful scenes containing multiple objects (the same rooms furnished) and over twice as strong as the response to arrays of multiple objects without three-dimensional spatial context (the furniture from these rooms on a blank background). This response is reduced if the surfaces in the scene are rearranged so that they no longer define a coherent space. We propose that the PPA represents places by encoding the geometry of the local environment.

Figure 2: Web-page generated for the paper (Epstein and Kanwisher, 1998) with abstract and Talairach coordinates displayed in a corner cube environment (Rehm et al., 1998).

Brede Database (Nielsen, 2003) inspired by the BrainMap database (Fox and Lancaster, 1994).

Presently 183 papers and the information used is:

Abstract of the article

3D coordinates representing change in brain activation or site of lesion: so-called Talairach coordinates (Talairach and Tournoux, 1988).

Non-negative matrix factorization

Non-negative matrix factorization (NMF) decomposes a non-negative data matrix $\mathbf{X}(N \times P)$ (Lee and Seung, 1999)

$$\mathbf{X} = \mathbf{W}\mathbf{H} + \mathbf{U}, \qquad (1)$$

where $\mathbf{W}(N \times K)$ and $\mathbf{H}(K \times P)$ are also non-negative matrices.

"Euclidean" cost function for

$$E_{\text{“eucl”}} = ||\mathbf{X} - \mathbf{W}\mathbf{H}||_F^2 \qquad (2)$$

Iterative algorithm (Lee and Seung, 2001)

$$\mathbf{H}_{kp} \leftarrow \mathbf{H}_{kp} \frac{\left(\mathbf{W}^{\mathsf{T}}\mathbf{X}\right)_{kp}}{\left(\mathbf{W}^{\mathsf{T}}\mathbf{W}\mathbf{H}\right)_{kp}} \qquad (3)$$

$$\mathbf{W}_{nk} \leftarrow \mathbf{W}_{nk} \frac{\left(\mathbf{X}\mathbf{H}^{\mathsf{T}}\right)_{nk}}{\left(\mathbf{W}\mathbf{H}\mathbf{H}^{\mathsf{T}}\right)_{nk}}. \qquad (4)$$

Partial least squares

One of the variations of partial least squares: Singular value decomposition of a inner product matrix (McIntosh et al., 1996)

$$\mathbf{ULV}^{\mathsf{T}} = \mathsf{svd}\left(\mathbf{X}^{\mathsf{T}}\mathbf{Y}\right) \tag{5}$$

Probably most suitable for data that is symmetric, i.e., both positive and negative.

"Non-negative partial least squares"

$$\mathbf{WH} = \mathsf{nmf}\left(\mathbf{X}^{\mathsf{T}}\mathbf{Y}\right) \tag{6}$$

Should get two non-negative matrices ($\mathbf{X}$ and $\mathbf{Y}$) as input.

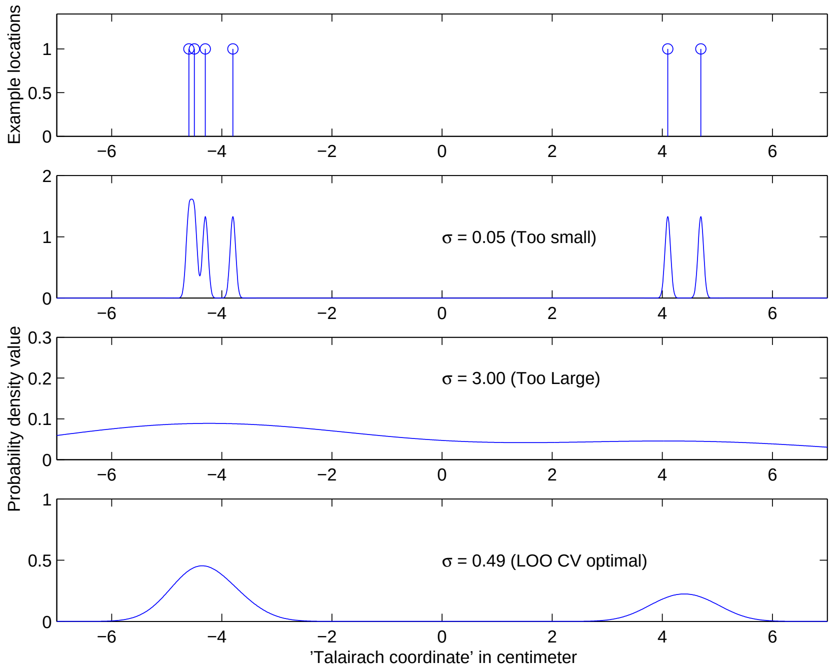
First matrix: Bag-of-words matrix

	'memory'	'visual'	'motor'	'time'	'retrieval'	...
Fujii	6	0	1	0	4	...
Maddock	5	0	0	0	0	...
Tsukiura	0	0	4	0	0	...
Belin	0	0	0	0	0	...
Ellerman	0	0	0	5	0	...
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$

Representation of the abstracts of the papers in a bag-of-words matrix: (abstract $\times$ words)-matrix: Each element counts of the frequency of a word occurring in an abstract text (Salton et al., 1975).

Exclusion of stop words: common words, brain anatomy, . . . Mostly words for brain function left (Nielsen et al., 2005).

Second matrix: Voxelization matrix



Regard the "locations" as being generated from a distribution $p(\mathbf{z})$, where $\mathbf{z}$ is in 3D Talairach space (Fox et al., 1997).

Kernel methods (N kernels centered on each location: $\boldsymbol{\mu}_n$) with homogeneous Gaussian kernel in 3D Talairach space $\mathbf{z}$

$$\hat{p}(\mathbf{z}) = \frac{(2\pi\sigma^2)^{-3/2}}{N} \sum_n^N e^{-\frac{1}{2\sigma^2}(\mathbf{z}-\boldsymbol{\mu}_n)^2}$$

σ^2 fixed ($\sigma = 1$cm) or optimized with leave-one-out cross-validation (Nielsen and Hansen, 2002).

Details

Coarse sampling of the volume with 8mm voxels: $\widehat{p}(\mathbf{z}) \equiv \mathbf{Y}$

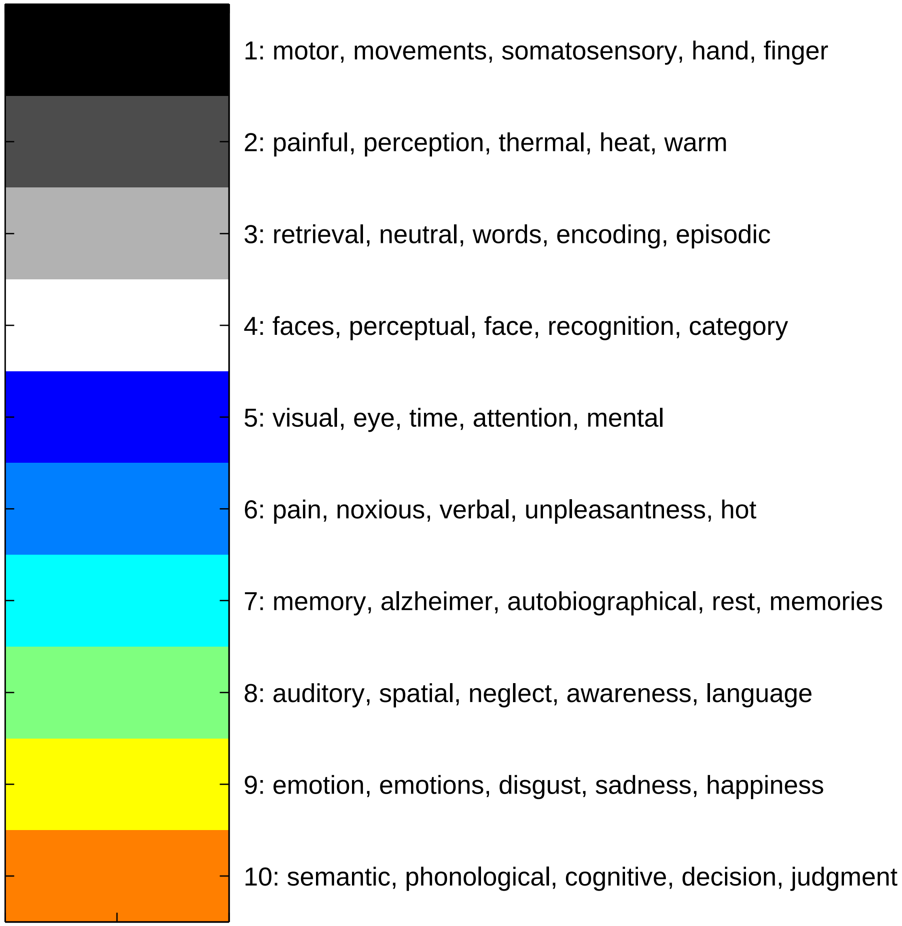
Restriction to gray matter regions using a anatomically labeled brain "AAL" (Tzourio-Mazoyer et al., 2002).

Number of components in NMF: Using a rule of thumb we select $K = \sqrt{N/2}$ (Mardia et al., 1979): $K = 10 \approx \sqrt{183/2}$.

10 runs of NMF with 1000 iterations each, with different initialization each time.

Exclusive assignment: Winner-takes-all function on $\mathbf{W}$ and $\mathbf{H}$.

Resulting NMF components



Loadings on words in $\mathbf{W}$

$\mathbf{W}(K \times P) = \mathbf{W}(10 \times 466)$, i.e., 10 components ("functions") and 466 words.

Most dominant functions listed at the top: motor, pain, retrieval, . . .

5 most loaded words listed for each function.

Dorsolateral surface view

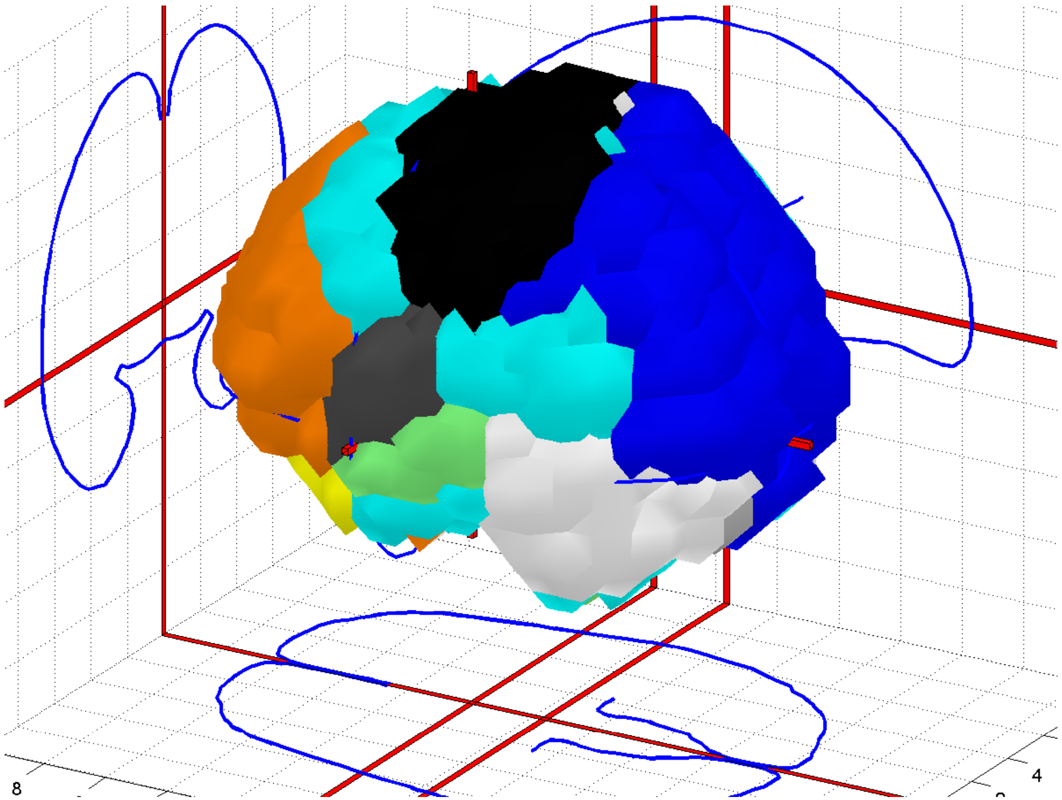


Figure 3: Labeled brain in corner cube environment (Rehm et al., 1998). Dorsolateral surface view seen from the left.

$\mathbf{H}$ in Talairach space: $\mathbf{H}(K \times Q) = \mathbf{H}(10 \times 9975)$, i.e., 10 components and 9975 voxels.

Occipital and parietal lobe: "visual", "eye".

Central sulcus: "Motor", "movements", "somatosensory".

Temporal cortex: "auditory", "spatial", "neglect"

Medial view

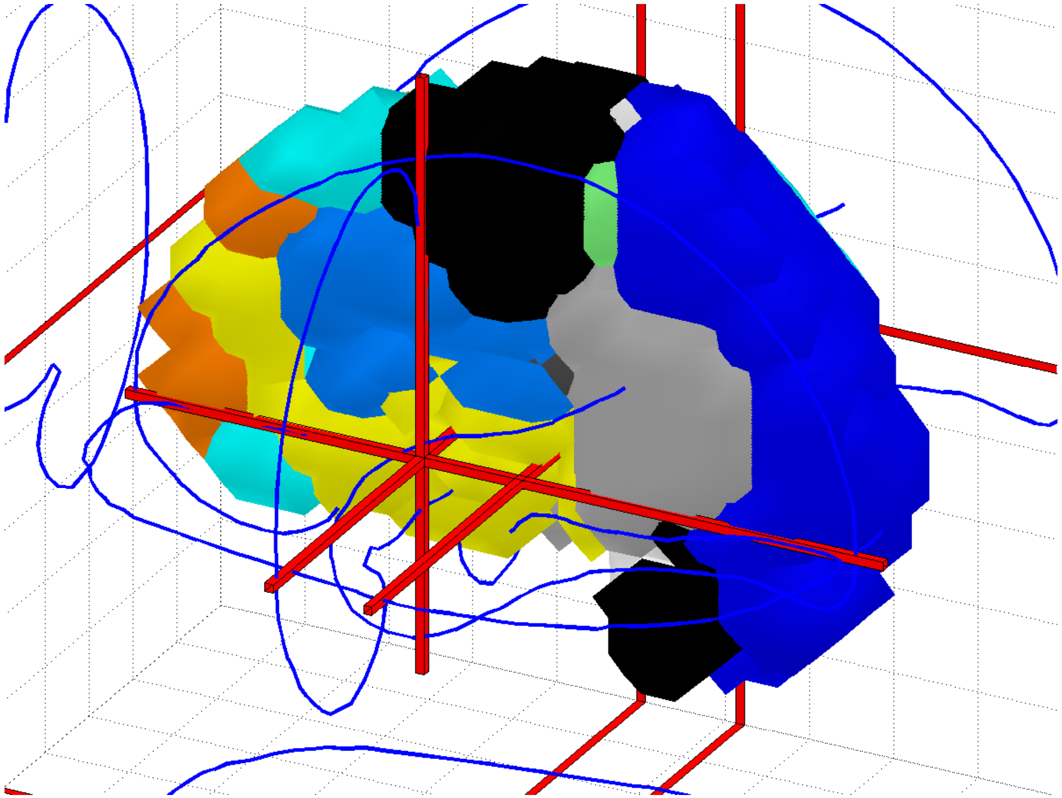


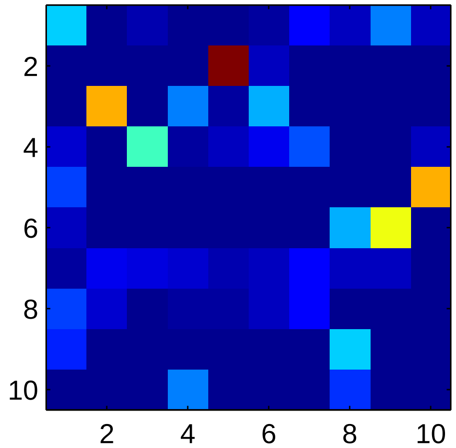
Figure 4: Medial surface view of the labeled right hemisphere. Seen from the left

"Memory" in posterior cingulate area. Probably due to the many articles about memory and the posterior cingulate in the Brede database. Episodic memory retrieval is associated with posterior cingulate (Cabeza and Nyberg, 2000).

"Emotion" in the medial frontal area, e.g., amygdala.

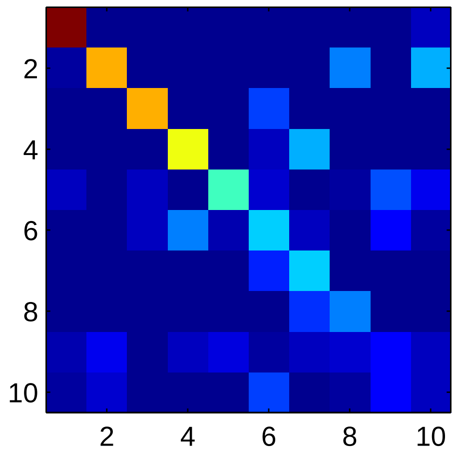
"Pain" in anterior cingulate, thalamus, insula. Previously noted: (Ingvar, 1999).

How stable are the results?



The parcellation varies between runs of the NMF and when different parts of the data set are used.

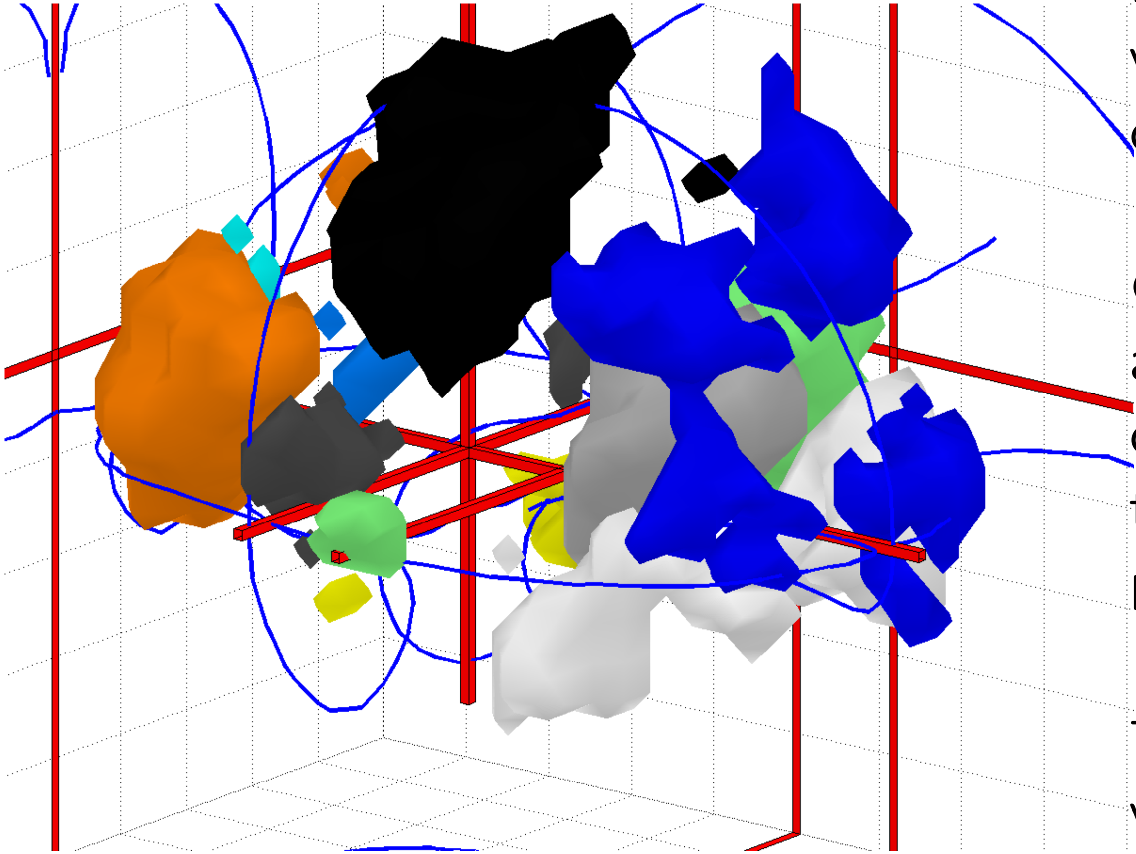
The different components are not matched between runs, e.g., the 2nd component in the first run might match the 5rd component in the second run.



It is possible to match the components, e.g., with the algorithm suggested by (Meilā, 2002).

The "confusion matrices" ($\mathbf{HH}^\mathsf{T}$) in the figure appear with one instance of half-split resampling between the 183 papers before and after sorting.

Consistent parcellation



Parcellation after masking those voxels that are consistently parcellated.

Consistent voxels determined as those that fall in the same component more than half the time during half-split resampling.

This results in 713 of the 9975 voxels.

Summary

It is possible to automatically perform a high-level coarse parcellation of the entire human brain.

The results appear in accordance with general consensus in human brain mapping.

We use the Brede Database and rely only on abstract and Talairach coordinate information.

We suggest "non-negative partial least squares" as a combination of non-negative matrix factorization and partial least squares.

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