Visualization and Analysis of 3D Functional Brain Images

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OVERVIEW

- The Functional Brain Imaging
- Neural Network with principal component preprocessing
- Neural Network generalization on fMRI-data (new)
- Saliency map with the entropic costfunction (new)
- The Saliency Map relations to other Analysis (NEW)
- Investigation of the Hidden Space (NEW)
- "Blob-integration"
- 3D Visualization with VRML (NEW)
- Conclusion

Not a Black Box

- Saliency Map
- Investigation of the representation in the hidden units

FUNCTIONAL BRAIN IMAGING

Segregation: Specific thoughts in specific brain regions
fMRI: functional Magnetic Resonance Imaging

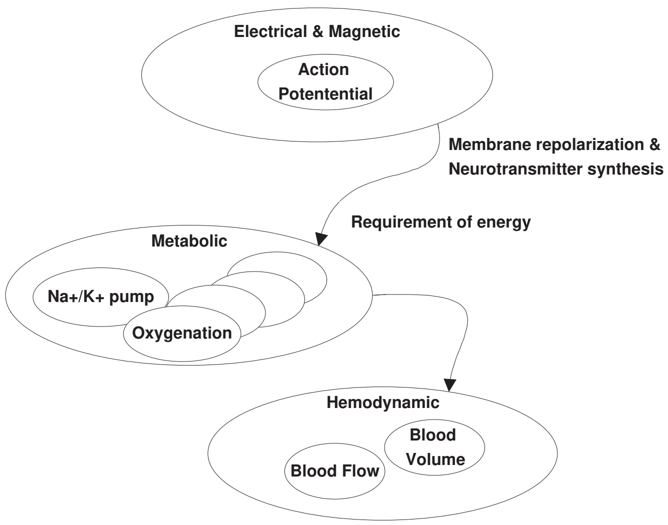
Advantage over PET

☺ Faster, volume acquisition 2.5 seconds

☺ Safer, no ionizing readiation

☺ Easy matching to anatomical image

☹ No separation of the physiological parameters

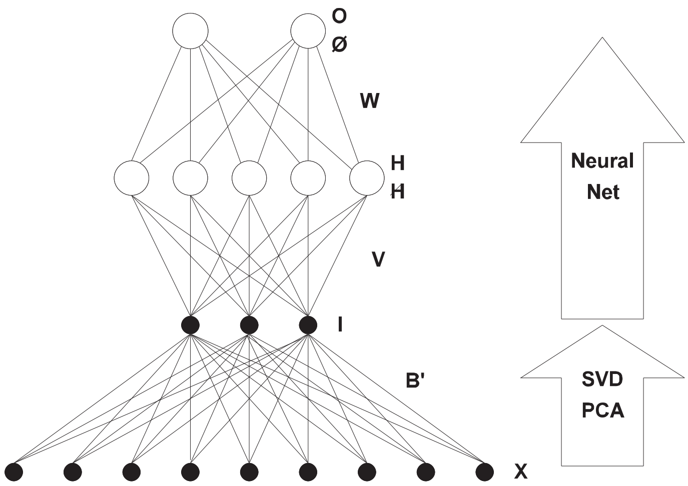


Method

- Establish a *baseline* — A rest state
- Activate the subject
- "Subtract" the two

Sequential finger opposition

NEURAL NETWORK ANALYSIS WITH PCA PREPROCESSING



Network equation

$$o_o^p = \tanh\left(\sum_{h=1}^{n_h} w_{oh} \tanh\left(\sum_{i=1}^{n_i} v_{hi} i_i^p + v_{h0}\right) + w_{o0}\right)$$

Costfunction

$$C = E + R$$

$$E_{entr} = \sum_{p=1}^{n_p} \sum_{o=1}^{n_o} \left[\frac{1}{2}(1 + d_o^p) \ln \frac{1 + d_o^p}{1 + o_o^p} + \frac{1}{2}(1 - d_o^p) \ln \frac{1 - d_o^p}{1 - o_o^p}\right]$$

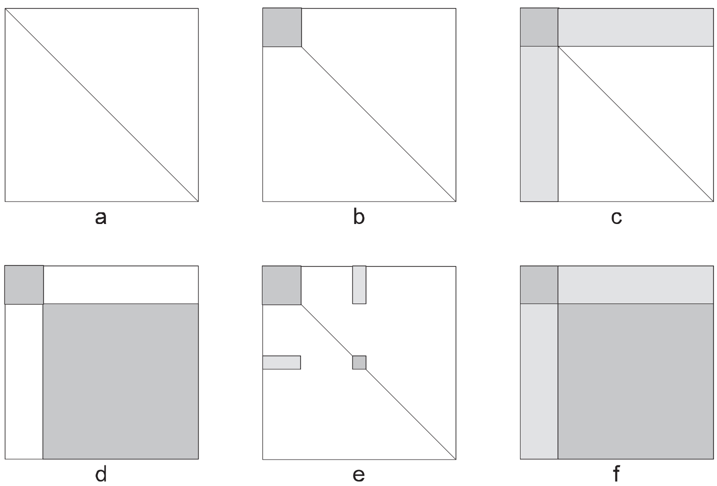
$$R_{qua} = \gamma_w \sum_{o=1}^{n_o} \sum_{h=1}^{n_h} w_{oh}^2 + \gamma_v \sum_{h=1}^{n_h} \sum_{i=1}^{n_i} v_{hi}^2$$

Optimization and generalization

- Newton methods
- Ordinary optimal brain damage
- Algebraic and empirical generalization error estimates

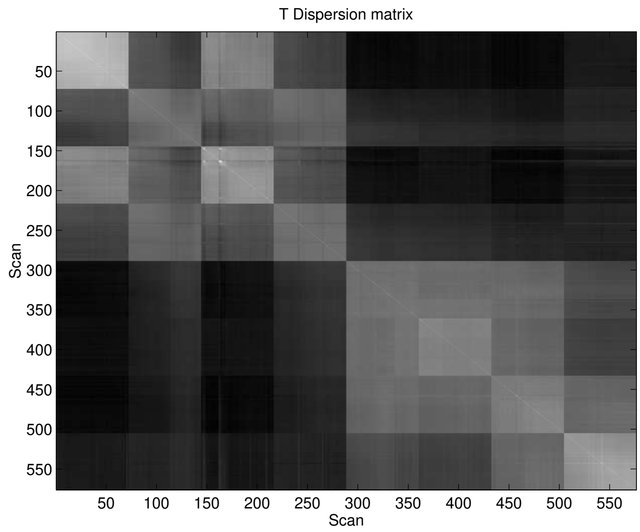
$$\Delta\mathbf{u} = -\left(\nabla^2_{\mathbf{uu}} C\right)^{-1} \nabla_{\mathbf{u}} C$$

$$\delta C_{\mathbf{u}} \approx \frac{1}{2} \delta\mathbf{u}^\top \frac{\partial^2 C}{\partial \mathbf{u}^2} \delta\mathbf{u}$$

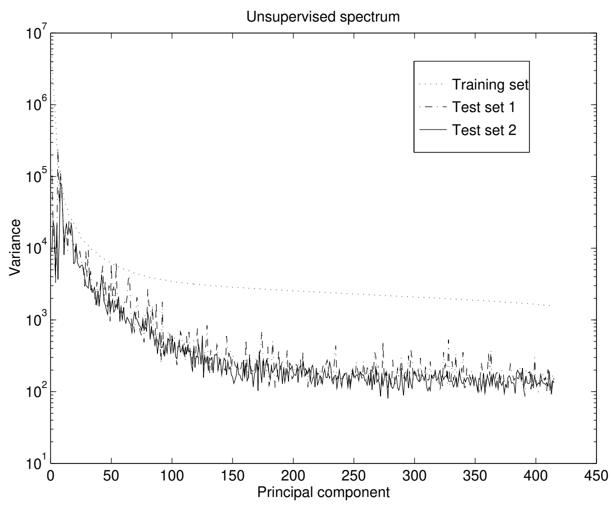


- Adaptive regularization with a newton step from zero

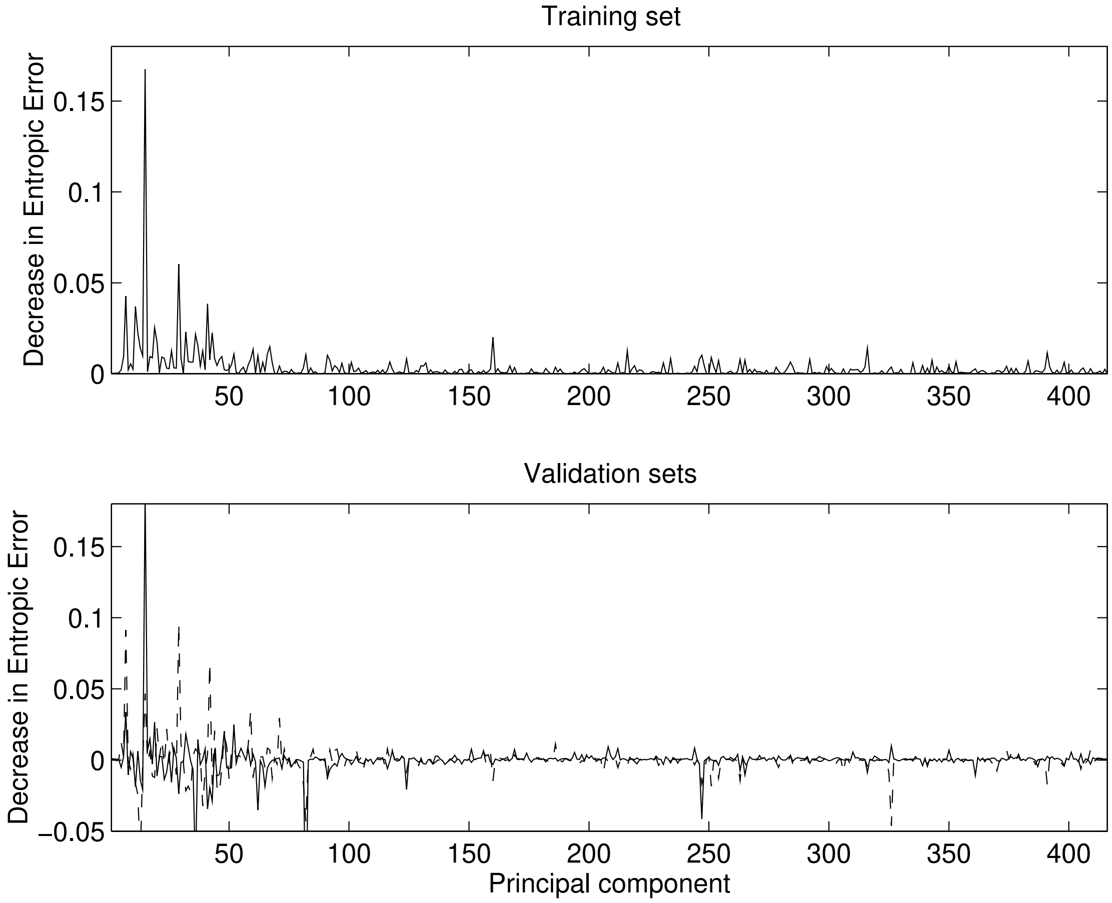
PRINCIPAL COMPONENT ANALYSIS



- Run effect
- Disturbance in the 3. run

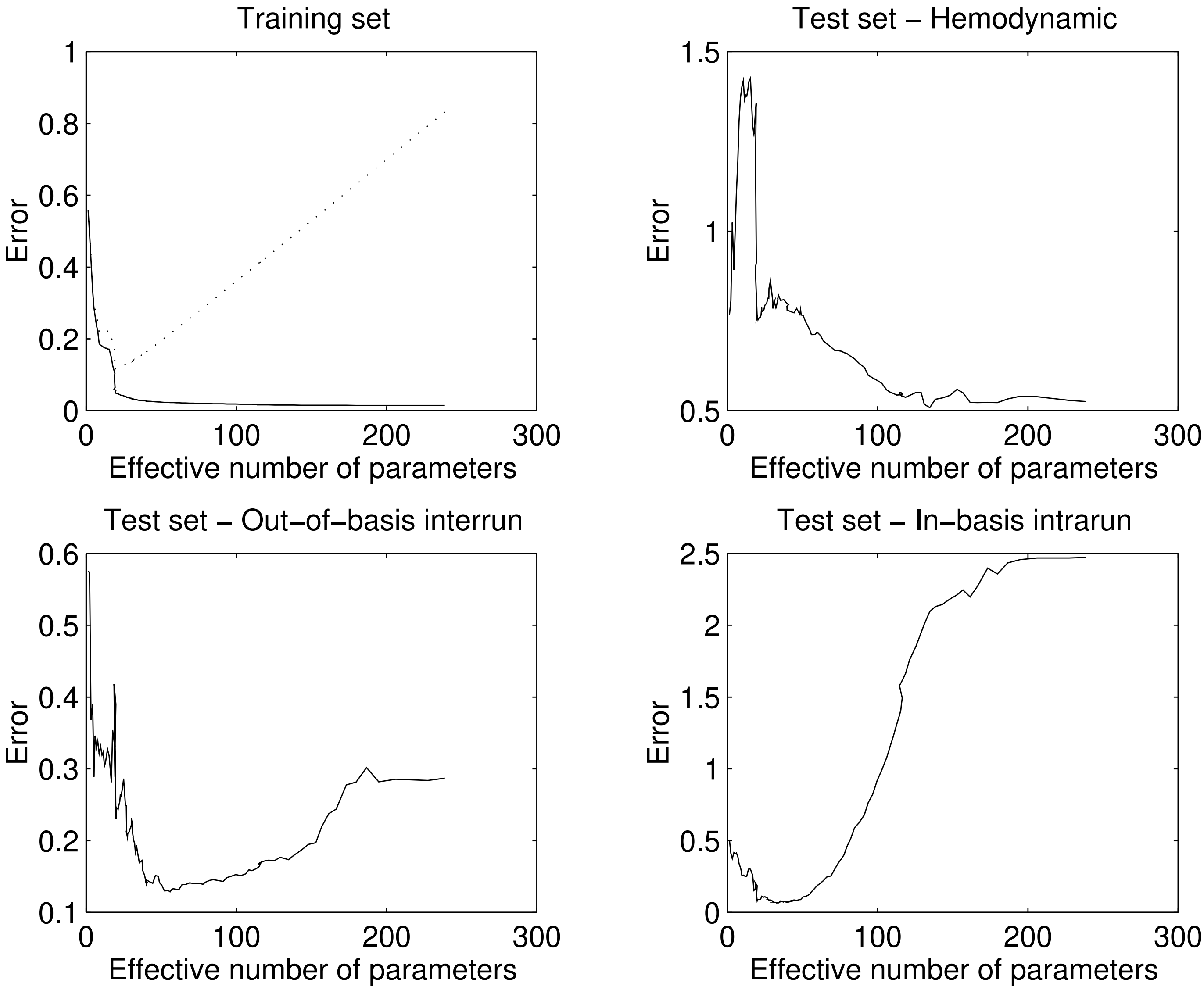


- Small projection on the higher principal component.

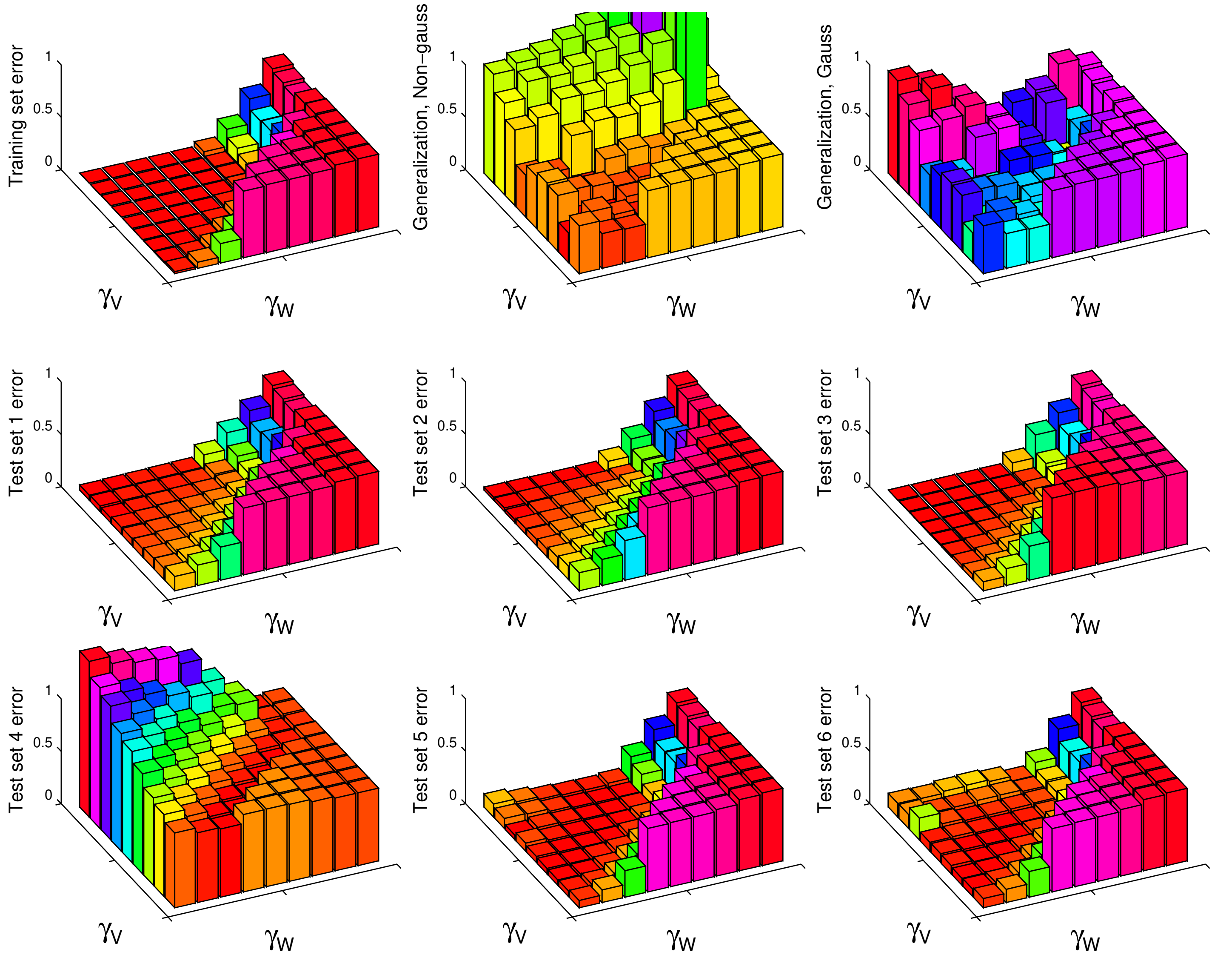


- Single subject: Largest variation: Run, Resampling.
- Not the largest paradigm signal in the principal component with the number of runs.

TRAINING AND GENERALIZATON



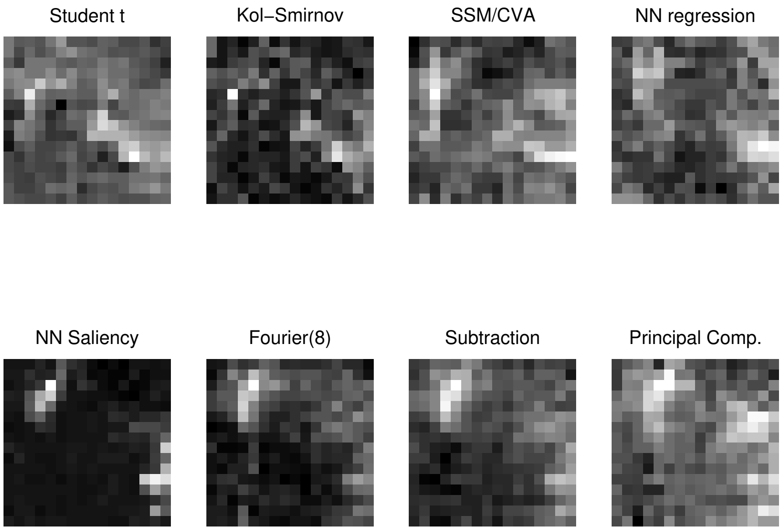
- Pseudo-gauss-newton and pseudo-newton different.
- Not able to generalize with scans containing the hemodynamic response (The fall flange).
- Generalization for interrun and intrarun scan is different.



➪ Do the low projection on the higher principal component somehow regularize.

SALIENCY MAP WITH THE ENTROPIC COSTFUNCTION

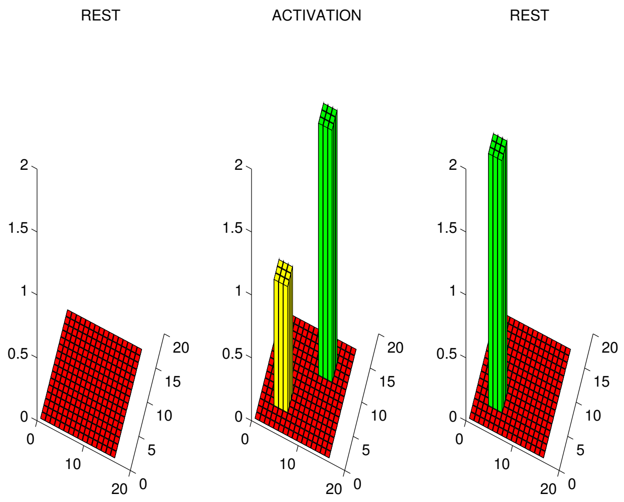
$$\begin{aligned}\delta C_{entr,x} \;=\; & \sum_p \sum_o \sum_h \sum_i \left(d_o^p - o_o^p\right) w_{oh} \left(1 - \left(h_h^p\right)^2\right) v_{hi} b_{ix} x_x^p \\ & + \frac{1}{2} \sum_p \sum_o \sum_i \left(1 - \left(o_o^p\right)^2\right) \left[\sum_h w_{oh} \left(1 - \left(h_h^p\right)^2\right) v_{hi}\right]^2 b_{ix}^2 \left(x_x^p\right)^2\end{aligned}$$

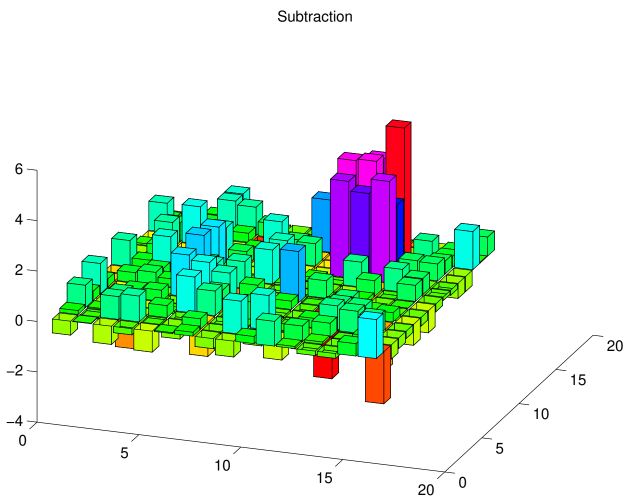


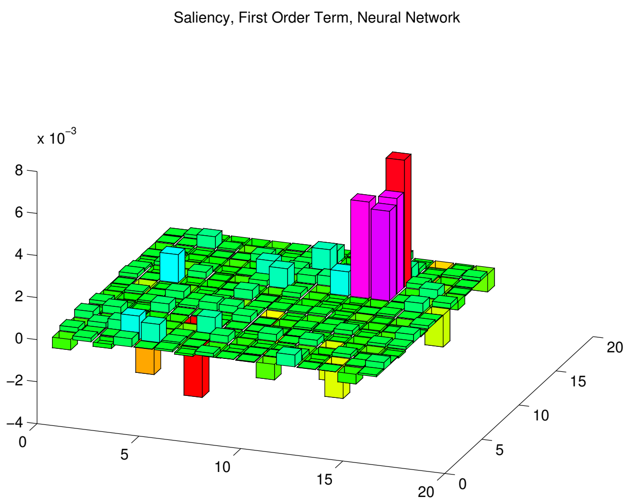
$$\begin{aligned}\delta C_{sq,x} \;&=\; \sum_i \sum_p u_i^2 b_{ix}^2 \left(x_x^p\right)^2 \\ &=\; \sum_p \left(b'\right)_x^2 \left(x_x^p\right)^2\end{aligned}$$

$$\delta C_{sq,x} = b_{ix}$$

⇨ ”Squared values” compared to eigenpictures


REST
ACTIVATION
REST
2
1.5
1
0.5
0
0
10
20
0
5
10
15
20

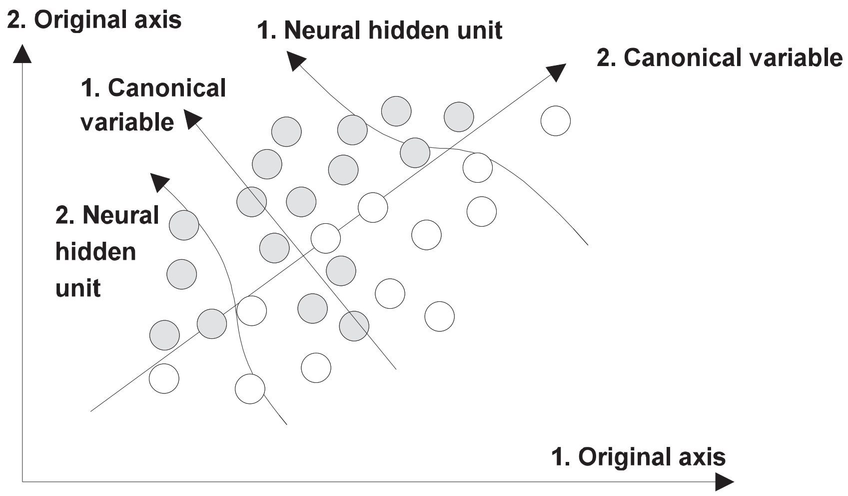

Subtraction
6
4
2
0
−2
−4
0
5
10
15
20
0
5
10
15
20


Saliency, First Order Term, Neural Network
x 10^{-3}
8
6
4
2
0
−2
−4
0
5
10
15
20
0
5
10
15
20

HIDDEN SPACE

$\boxed{\text{Look at the values of the patterns in the hidden units}}$

$$h_h^p = \tanh\left(\sum_{i=1}^{n_i} v_{hi} i_i^p + v_{h0}\right)$$



Somehow similar to canonical variance analysis

Methods

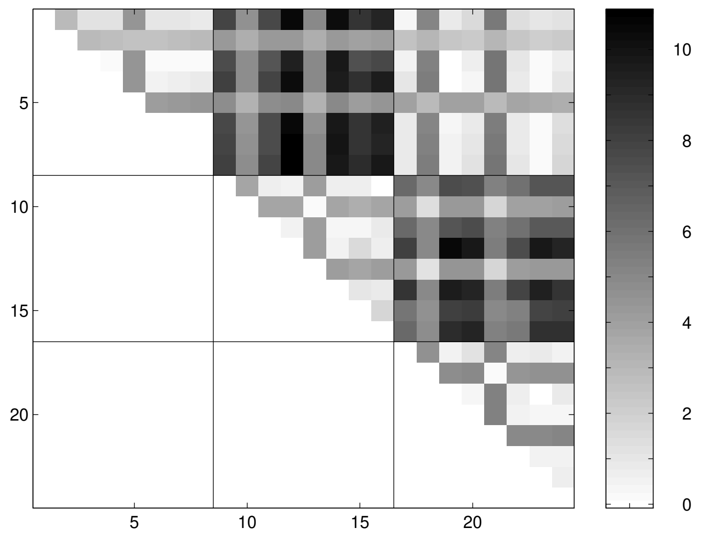
- Second Moment Statistics
- Visualize
- Projection forward or backward

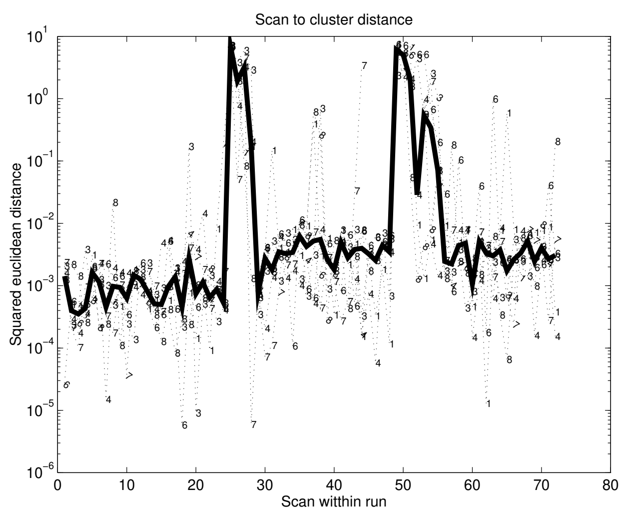
Backprojection

$$\mathbf{x}^{\mathcal{H}} = \mathbf{B}\left(\mathbf{V}^{\top}\mathbf{V}\right)^{\dagger}\mathbf{V}^{\top} atanh\left(\mathbf{h}\right)$$

Statistics

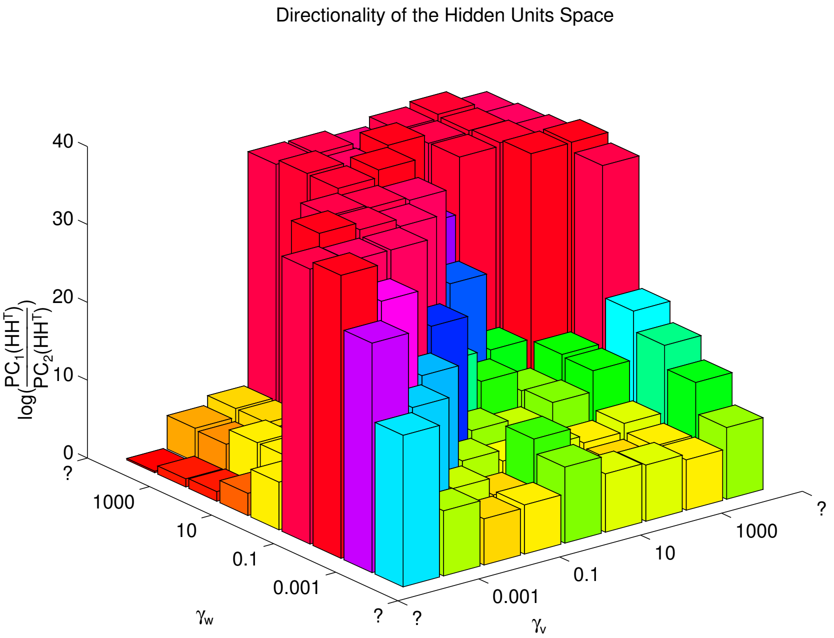
- Pattern to cluster
- Cluster to cluster: Example: All first rest states, Rest state run 1.

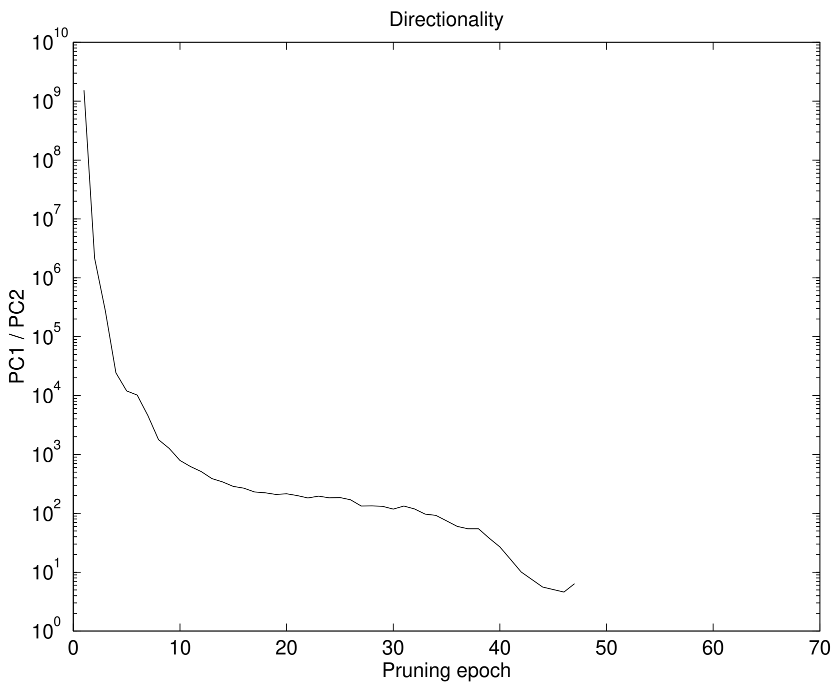




Directionality

$$D = \frac{PC_1\left(\mathbf{H}\right)}{PC_2\left(\mathbf{H}\right)}$$

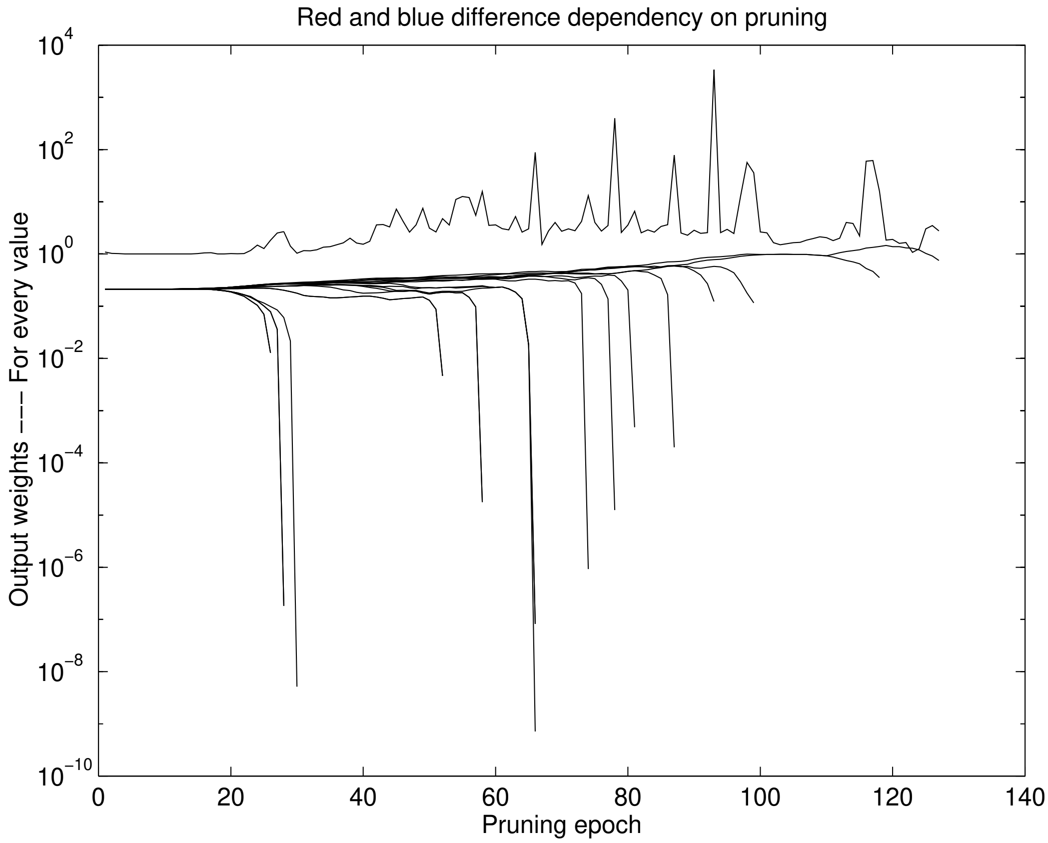




"FIREWORKS UNITS"

Hypothesis: Rest states are the same

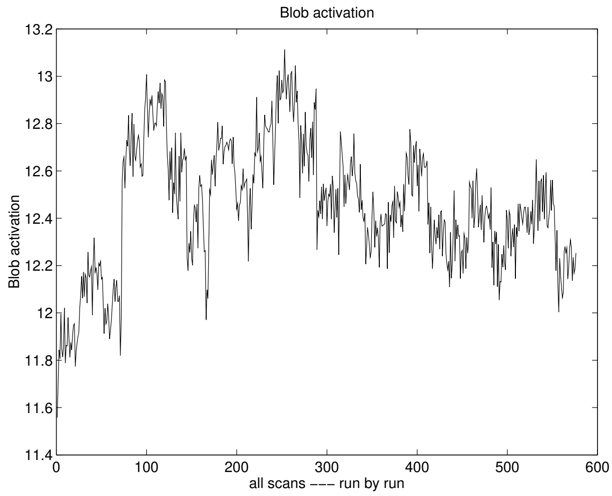
$$D^2 = \left(\bar{\mathbf{h}}_1 - \bar{\mathbf{h}}_2\right) \mathbf{S}^{-1} \left(\bar{\mathbf{h}}_1 - \bar{\mathbf{h}}_2\right)^\top$$

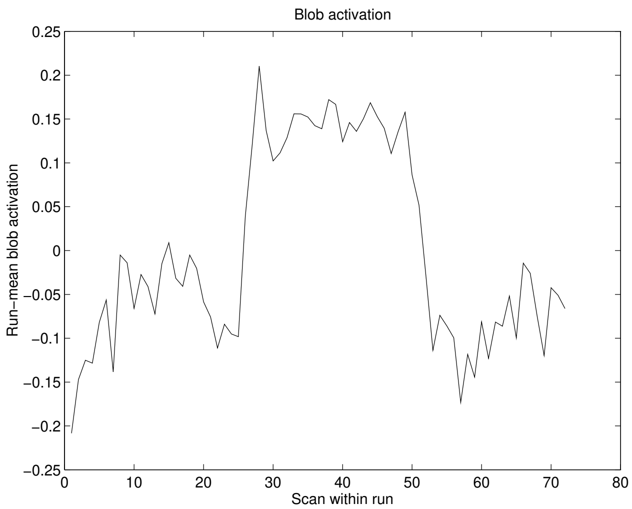


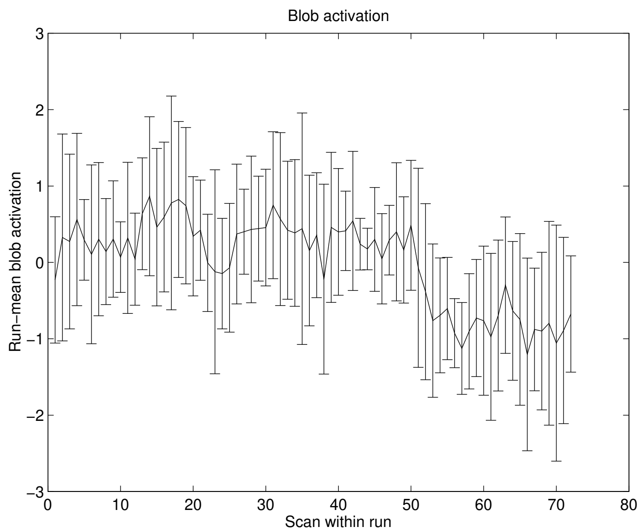
➪ The decaying weight contains information about the difference in the rest states.

"BLOB INTEGRATION"

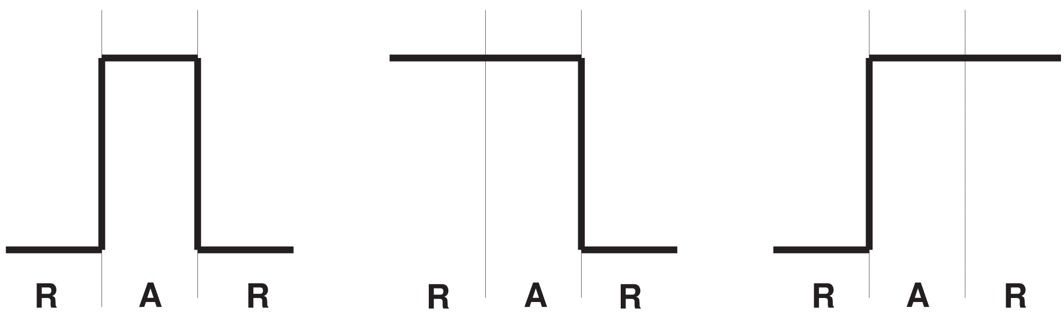
- Find an interesting blob: Segmentation, ROI
- Blob investigation: Relation to the paradigm.







- The hidden space backprojection and second order saliency pinpointed an interesting blob.



3D VISUALIZATION

- 50 percent more dimensions
- Orientation harder (orthographic camera, grid)
- Depth cue by motion

Types of 3D visularization methods

- Volume graphics
- Surface graphics

VRML

- Static 3D models
- Polygons
- Lines, points, text
- Texture, light, color
- Portable, internet ready
- Inline, hyperlinks

CONCLUSION

- I this single subject study the largest variation is not due to the paradigm. Variation due to the paradigm is in the higher principal components.
- The neural network analysis with preprocessing of singular value decomposition / principal component analysis is able to intrasession, interrun, out-of-basis generalize.
- In fMRI studies the fast sampling will cause some scans to contain hemodynamic response. These "misclassified" scan confuse the entropic costfunction of the neural network.
- A saliency map was found: Blobs in accordance with the result of other studies. The saliency map has a higher contrast.
- The behaviour of the patterns (scans) in the space spanned by the hidden units has been investigated: Clustering, Backprojected.
- Visualization in VRML.