DTU

610

Space-time analysis of fMRI by feature space clustering

C. Goutte, F.Å. Nielsen, L.K. Hansen — Department of Mathematical Modelling, Technical University of Denmark
C. Svarer — Neurobiology Research Unit, Copenhagen University Hospital, Denmark
E. Rostrup — Danish Research Center for MR, Hvidovre, Denmark

DTU

610

Abstract

- Clustering fMRI time series in groups of voxels (regions) with similar activation properties.
- Extracting features, each representing part of the "information".
- Use the cross-correlation function instead of the raw fMRI time series.

fMRI time series

The fMRI signal: hemodynamic response to focal neural activity. It is a combination of several interacting components:

- actual response,
- neuronal activations,
- global components (breathing, etc.).

Signal correlated in *time* and *space* with both *short-term* and *long-term* correlations.
Stimulus $p(t)$ (usually square wave)
$\Longrightarrow$ fMRI time series $y(t)$

Feature extraction

1. Calculate the cross-correlation function

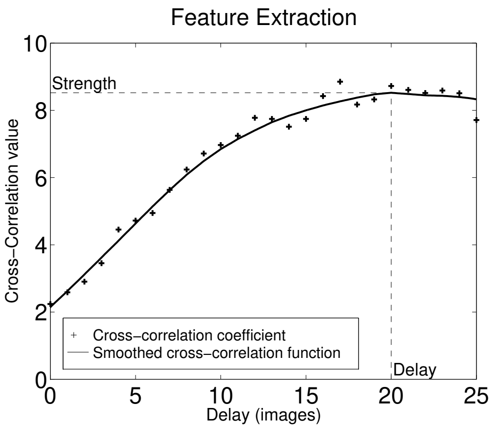
$$x(t) = \frac{1}{P}\sum_{u=1}^{P} y(u)p(u-t)$$

Note: x is *not* the correlation coefficient!

2. Extract the features (see figure below)

- Delay,
- Strength,
- Energy given by $\sum_{t=1}^{P} x^2(t)$.

Smooth noisy $x(t)$ with Epanechnikov kernel:



K-means Clustering

Clustering is an exploratory data analysis technique.
The K-means algorithm is a simple non-parametric clustering method.

1. Initialize K clusters $k = 1 \dots K$, with centers $C_k^{(0)}$. Iteration $i = 0$.
2. Assign each data vector x_j to the cluster k with the nearest center $C_k^{(i)}$.
3. Set new cluster centers $C_k^{(i+1)}$ to the center of gravity of the cluster members:
$C_k^{(i+1)} = E\{x_j\}_{x_j \in k}$
This formula can also be modified to use the median and/or include a smoothing term.
4. Goto step 2 until convergence.

Convergence is usually very fast: only few iterations are needed.
However, the result is very dependent on two factors:

- The number of clusters used,
- the initial setting of the centers.

Experiments

The data has been collected in the following situation:

subjects :	single subject.
task :	visual stimulation with a full-field checker board reversing at 8 Hz during activation.
modality :	1.5T EPI ($T2^*$)
paradigm :	35-30-35 images.
sampling :	3 images per second.
location :	para-axial orientation parallel to calcarine sulcus.
slice :	128x128 voxels.
ROI :	71x91 voxels.
voxel size :	3.1x3.1x8mm.

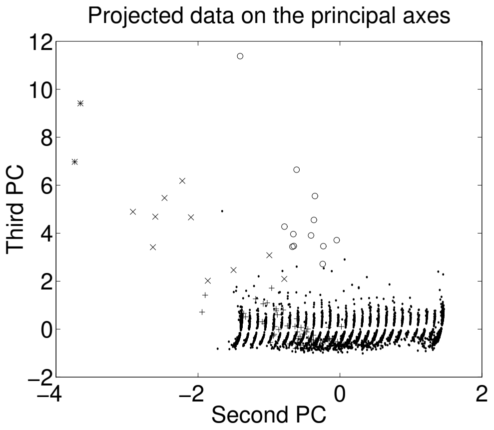
K-means experiments

K-means with 9 clusters resulted in:

- · 5 clusters for 98% of voxels non-activated
- ∗,x,+ 3 clusters for different levels of positive activation
- o 1 cluster with “negative” activation

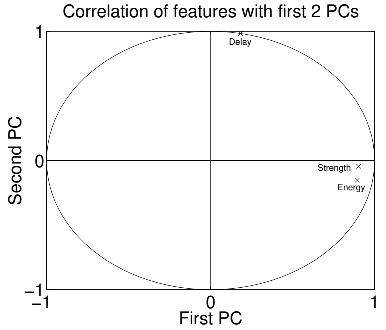
Implementation

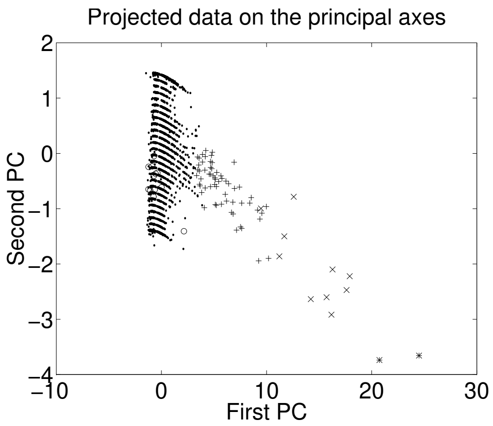
The algorithm is part of a Matlab toolbox currently under development at DTU.

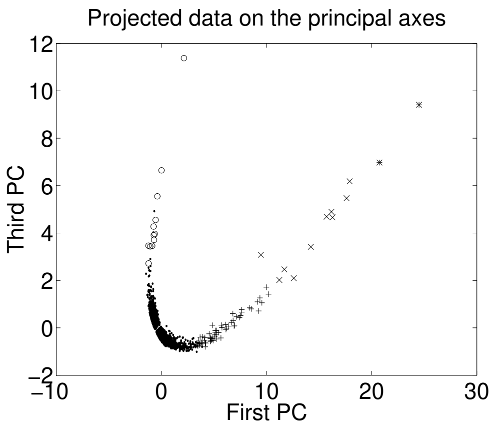


Principal Components projections

The figure below shows the relations between the principal components and the features.

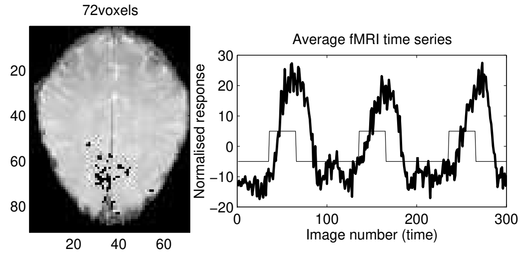


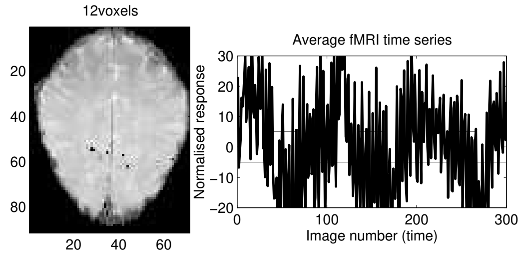




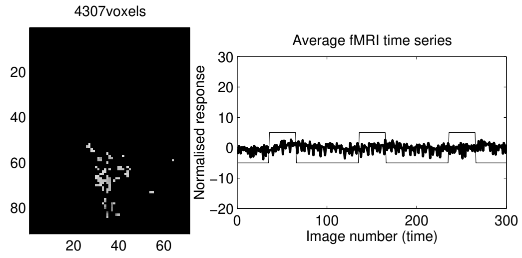
Activation maps

The figures below show the positively and negatively activated voxels respectively.

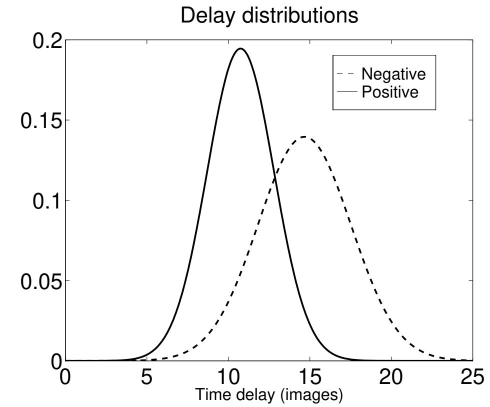




The figure below shows the non-activated voxels.



Delay analysis



Average delay of

5s for positively activated voxels
3.5s for negatively activated voxels

This is significant at the 2% level (KS test)

Conclusion

By means of various clustering techniques the task of identifying regions with similar response can be automated. In the presented case the cluster analysis of feature space provides an original scheme for mapping the spatio-temporal distribution of focal neural activation to a low-dimensional feature space.

References

B. Ripley, *Pattern Recognition and Neural Networks*, Cambridge, 1996.
P. Toft et al., *NeuroImage*, 4:5, S456, 1997.
C. Goutte et al., submitted, 1998.