Center for Cognitive Neuroscience

Model-Free Artifact Removal:

Denoising with MELODIC ICA

by Matt Schreiner

(Adapted from material created by Leonardo Christov-Moore)

AGENDA

- INTRODUCTION AND OVERVIEW
- DENOISING TUTORIAL
- WORKSHOP TIME!

Variability in FMRI

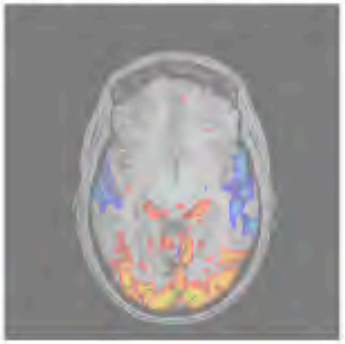
Experiment

suboptimal event timing, inefficient design, etc.

Physiology

secondary activation, ill-defined baseline, resting-fluctuations etc.

Interpretation of final results



Analysis

filtering & sampling artefacts, design misspecification, stats & thresholding issues etc.

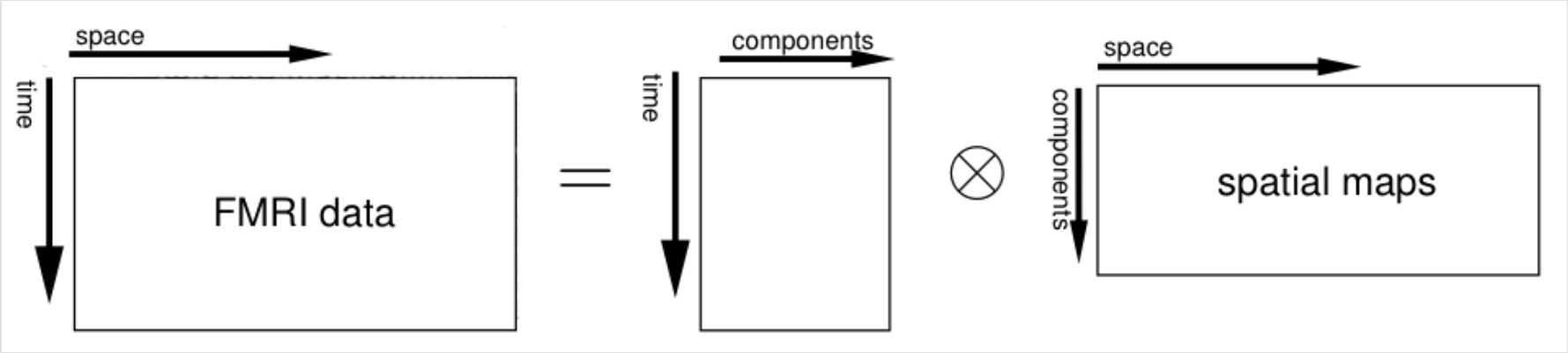
MR Physics

MR noise, field inhomogeneity, MR artefacts etc.

http://www.fmrib.ox.ac.uk/fslcourse/lectures/melodic.pdf

WHAT IS ICA?

- Independent Component Analysis (ICA)
- Computational method for separating a multivariate signal into its source components (ICs)
- Attempts to maximize the statistical independence of the estimated Ics.



(http://fsl.fmrib.ox.ac.uk/fsl/fslwiki/MELODIC)

WHAT IS MELODIC?

- FSL's implementation of ICA
- Can be used for group-level ICA, as well as **single-session ICA (ssICA)**

```
Part of FSL (build 506)
MELODIC (Version 3.14)
 Multivariate Exploratory Linear Optimised Decomposition into Independent Components

Author: Christian F. Beckmann
 Copyright(c) 2001-2013 University of Oxford

Usage:
 melodic -i <filename> <options>
                 to run melodic
 melodic -i <filename> --ICs=melodic_IC --mix=melodic_mix <options>
                 to run Mixture Model based inference on estimated ICs
 melodic --help

Compulsory arguments (You MUST set one or more of):
        -i,--in input file names (either single file name or comma-separated list or text file)

Optional arguments (You may optionally specify one or more of):
```

WHAT IS MELODIC?

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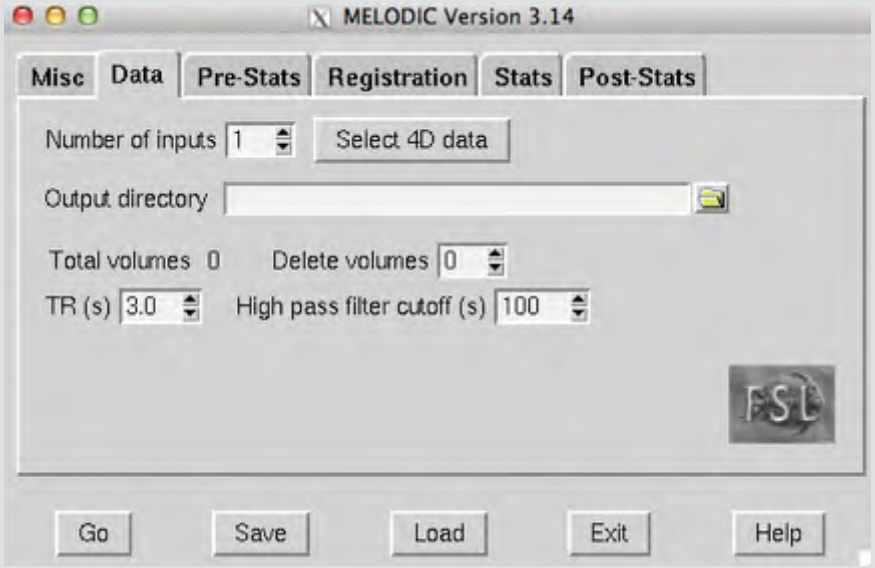
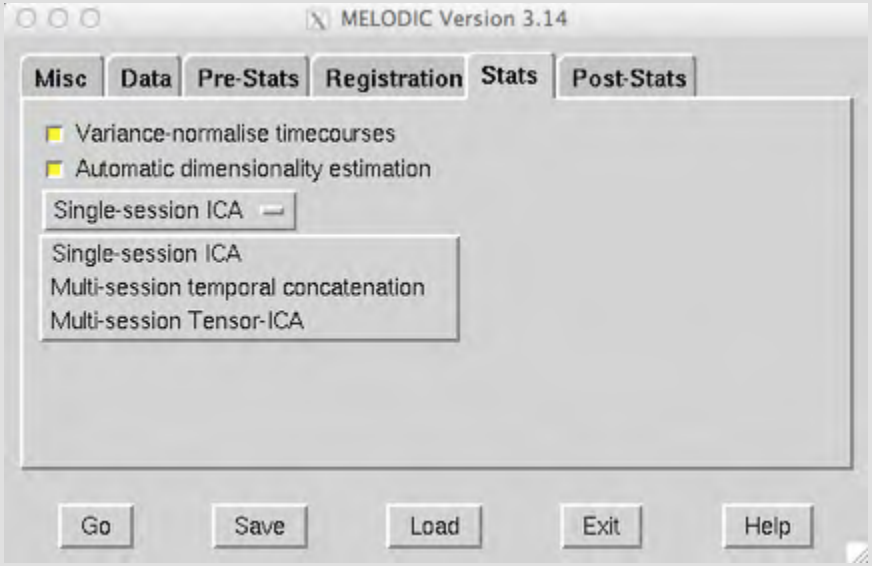
- Can be used for group-level ICA, as well as **single-session ICA (ssICA)**





DENOISING WITH ICA via MELODIC

1. Run MELODIC on a single subject

2. Examine output to identify components as **SIGNAL** or **NOISE**

3. Regress **NOISE** components out of subject's data

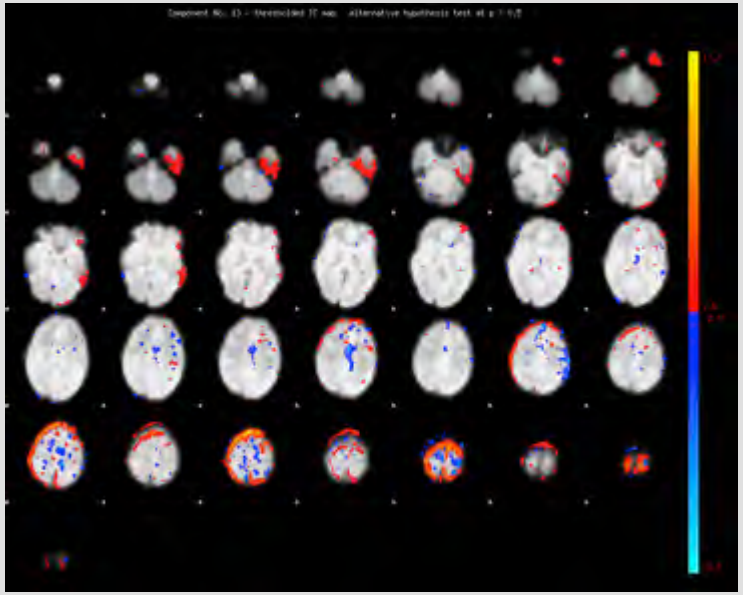
4. Utilize **denoised data** for further analysis

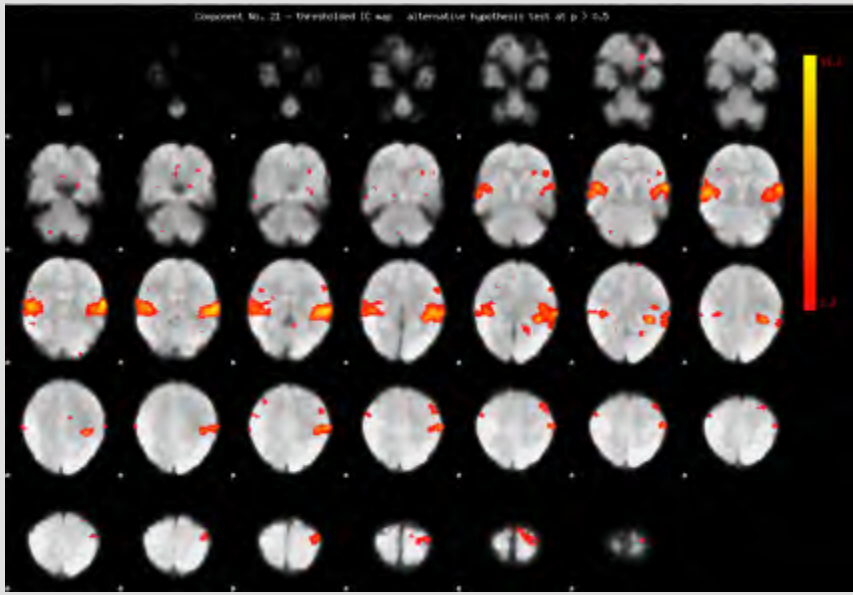
BUT HOW DO WE IDENTIFY

NOISE ?

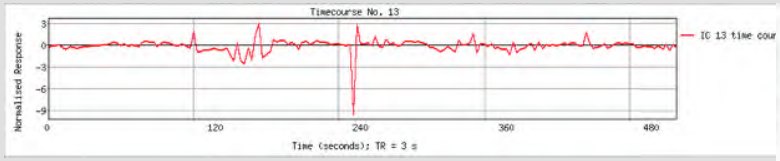
IDENTIFYING STRUCTURED NOISE

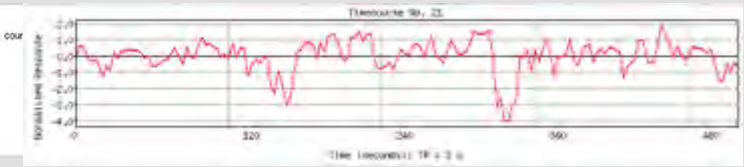
Spatial Map



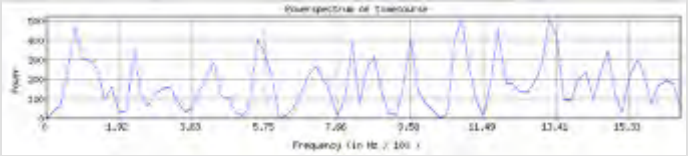


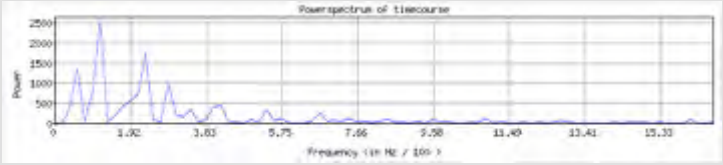
Time series



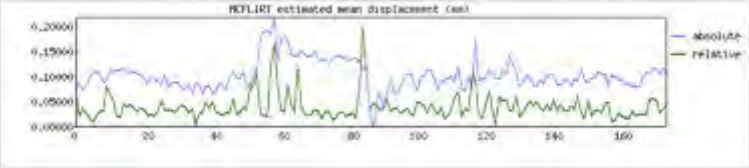


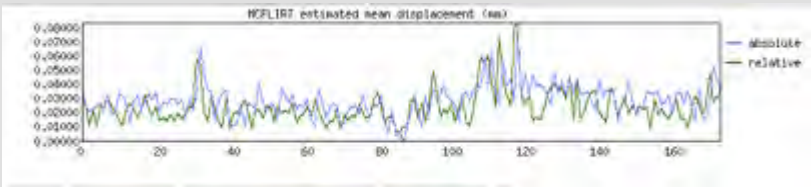
Power Spectrum





Motion plots





ICA Denoising: Standardization of practice

Visual inspection of independent components: Defining a procedure for artifact removal from fMRI data

Robert E. Kelly Jr.[a,*], George S. Alexopoulos[a], Zhishun Wang[e], Faith M. Gunning[a], Christopher F. Murphy[a], Sarah Shizuko Morimoto[a], Dora Kanellopoulos[a], Zhiru Jia[a], Kelvin O. Lim[d], Matthew J. Hoptman[b,c]

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Artifacts
Structured noise
Independent component (IC) labeling

ABSTRACT

Artifacts in functional magnetic resonance imaging (fMRI) data, primarily those related to motion and physiological sources, negatively impact the functional signal-to-noise ratio in fMRI studies, even after conventional fMRI preprocessing. Independent component analysis' demonstrated capacity to separate sources of neural signal, structured noise, and random noise into separate components might be utilized in improved procedures to remove artifacts from fMRI data. Such procedures require a method for labeling independent components (ICs) as representing artifacts to be removed or neural signals of interest to be spared. Visual inspection is often considered an accurate method for such labeling as well as a standard to which automated labeling methods are compared. However, detailed descriptions of methods for visual inspection of ICs are lacking in the literature. Here we describe the details of, and the rationale for, an operationalized fMRI data denoising procedure that involves visual inspection of ICs (96% inter-rater agreement). We estimate that dozens of subjects/sessions can be processed within a few hours using the described method of visual inspection. Our hope is that continued scientific discussion of and testing of visual inspection methods will lead to the development of improved, cost-effective fMRI denoising procedures.

Identifying Structured Noise

1. Spatial Map

Does the spatial component look biological? Is it localized to white matter, sinuses, ventricles, or the edges of the brain? Does it respect anatomical boundaries?

2. Time course

Are there drifts, large spikes, or a saw-tooth pattern?

3. Power Spectrum

Is more than 50% of the power in the frequency spectrum above 0.1Hz?

MELODIC Report

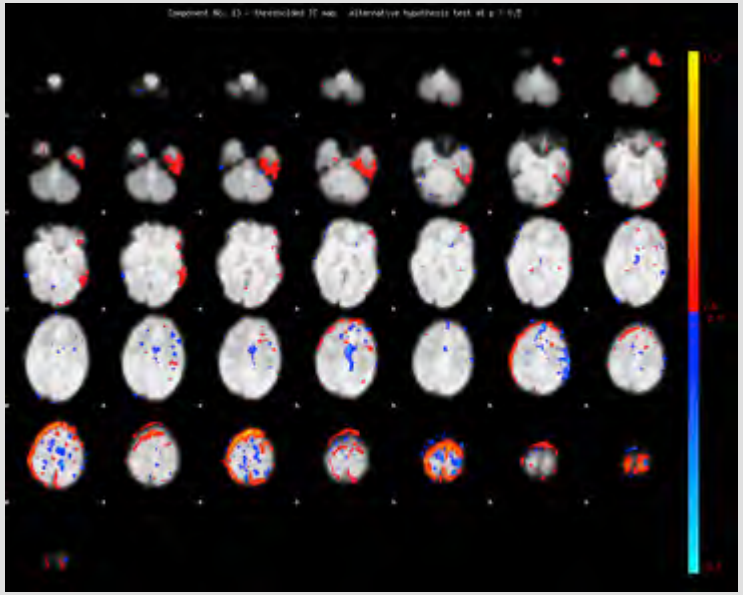
4. Motion time series

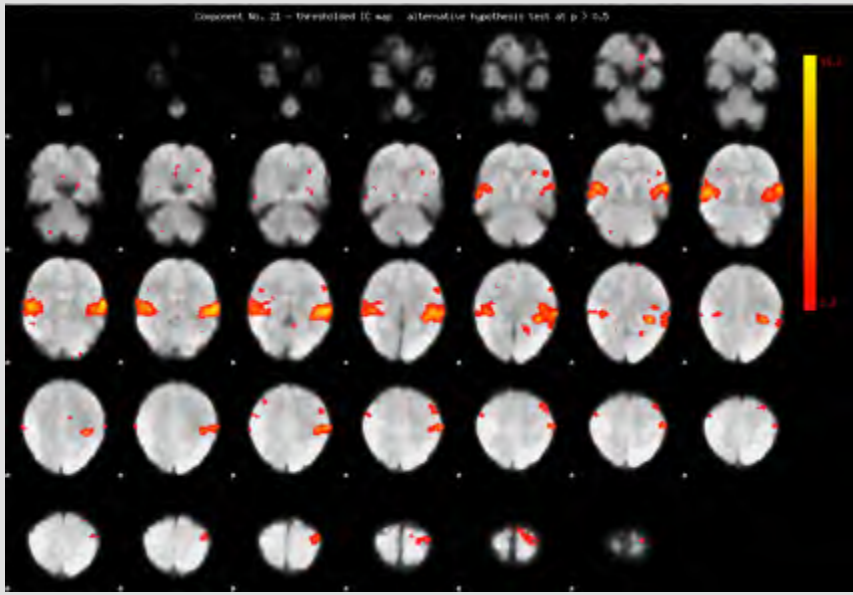
Is the component highly correlated with subject motion?

FEAT Report

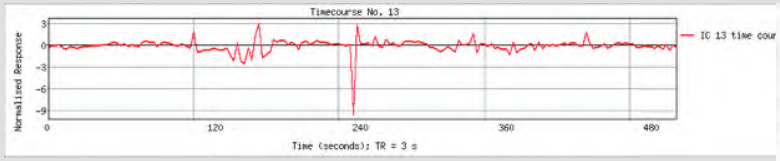
Identifying Structured Noise

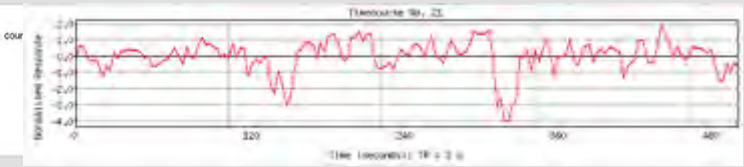
Spatial Map



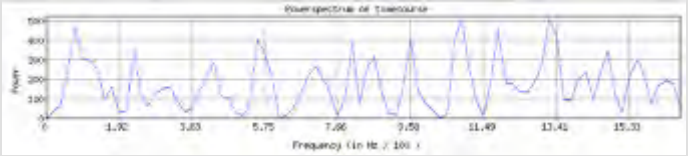


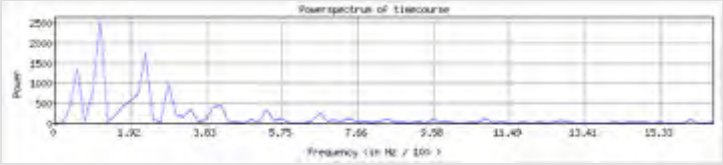
Time series





Power Spectrum





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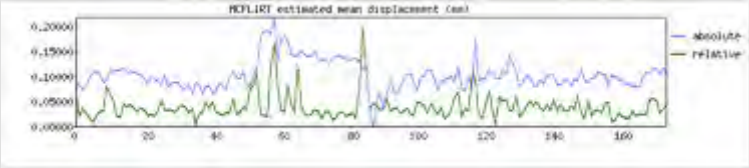
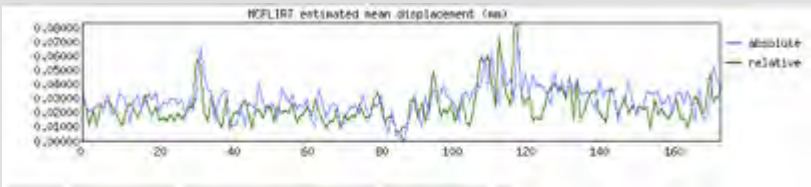


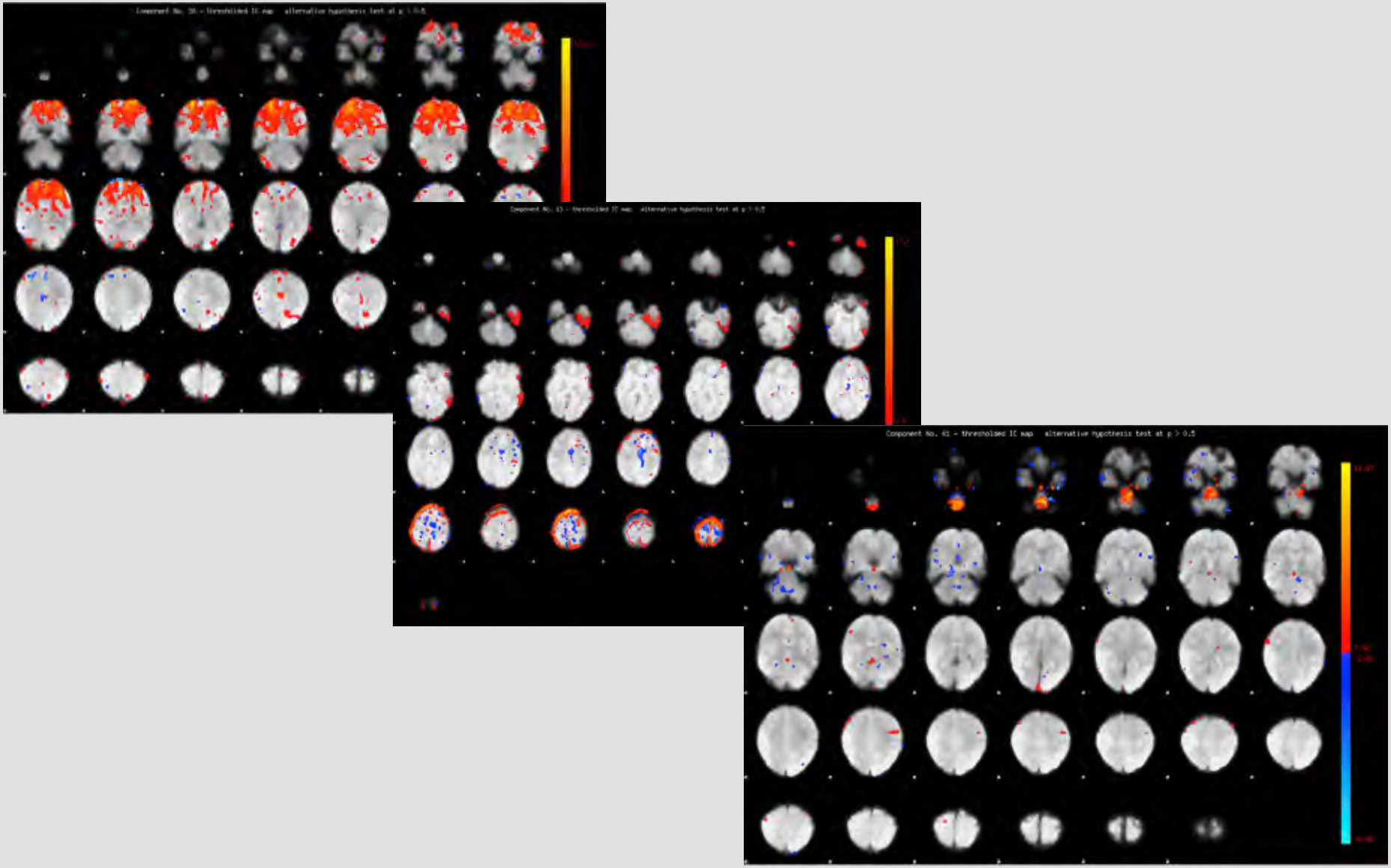


Identifying Structured Noise

Examples of **NOISE** and **SIGNAL**

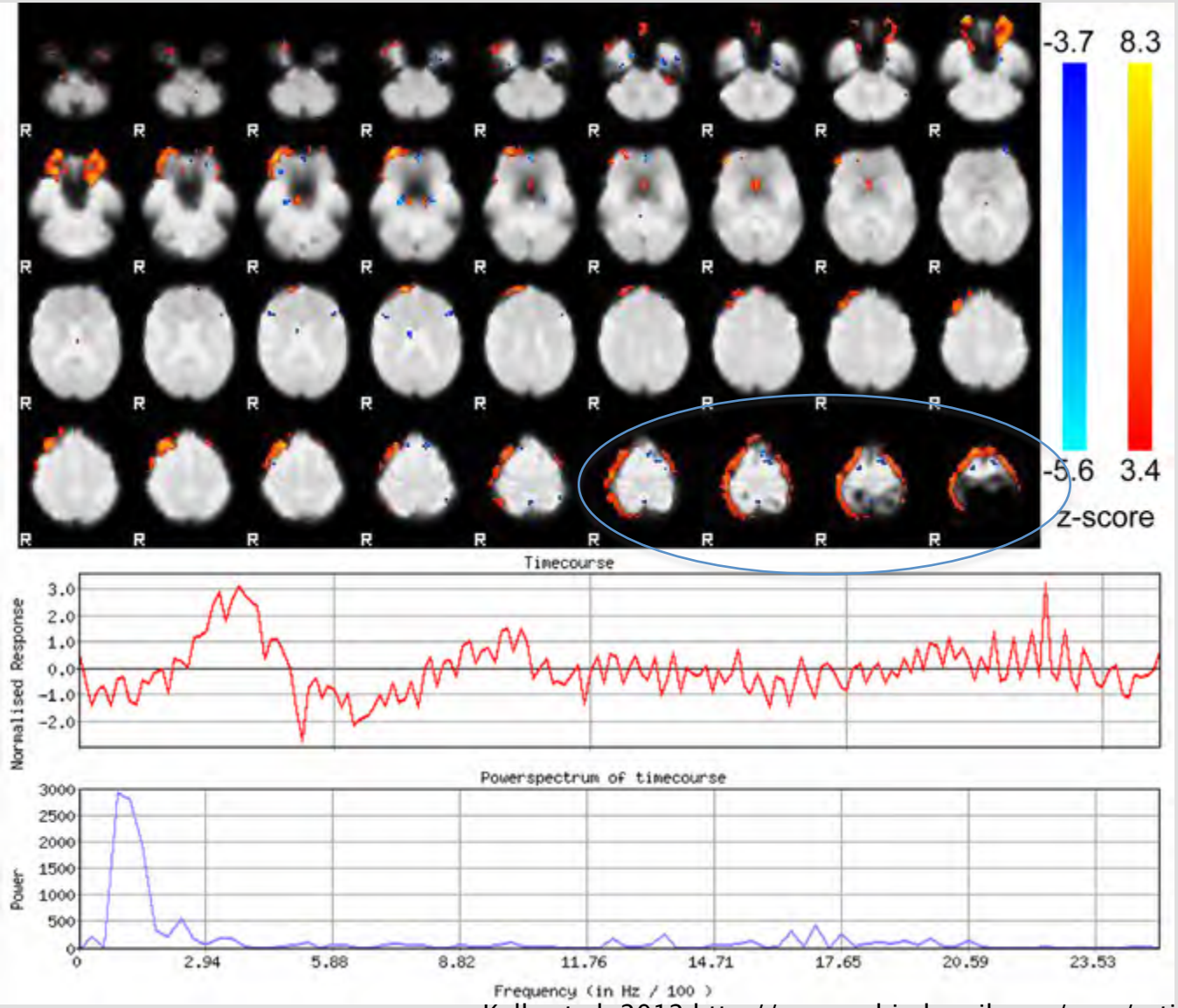
components from various ICA sessions

Spatial Maps



“Ring” pattern

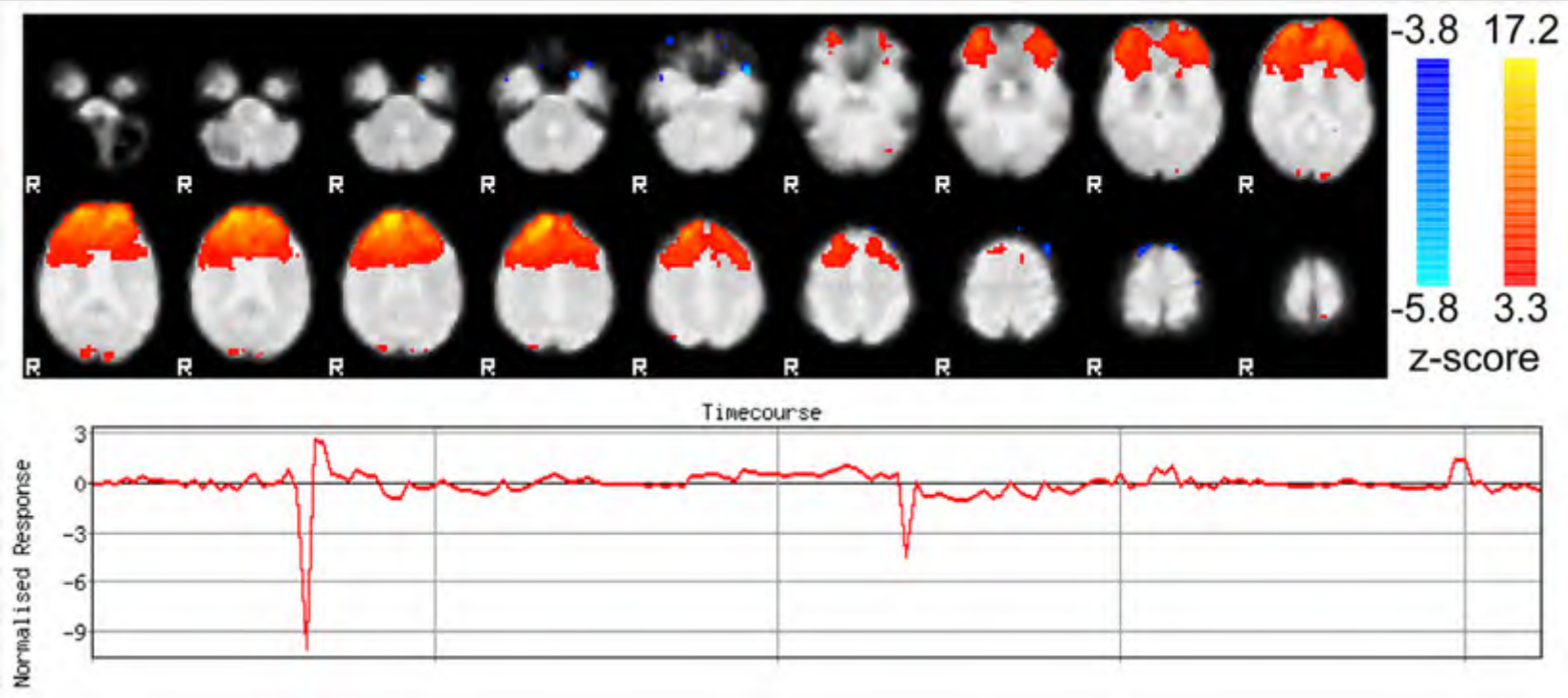
Due to head motion



Kelly et al.,2012 http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3299198/

“Slabbing”: large areas of activation that do not respect WM/GM boundaries

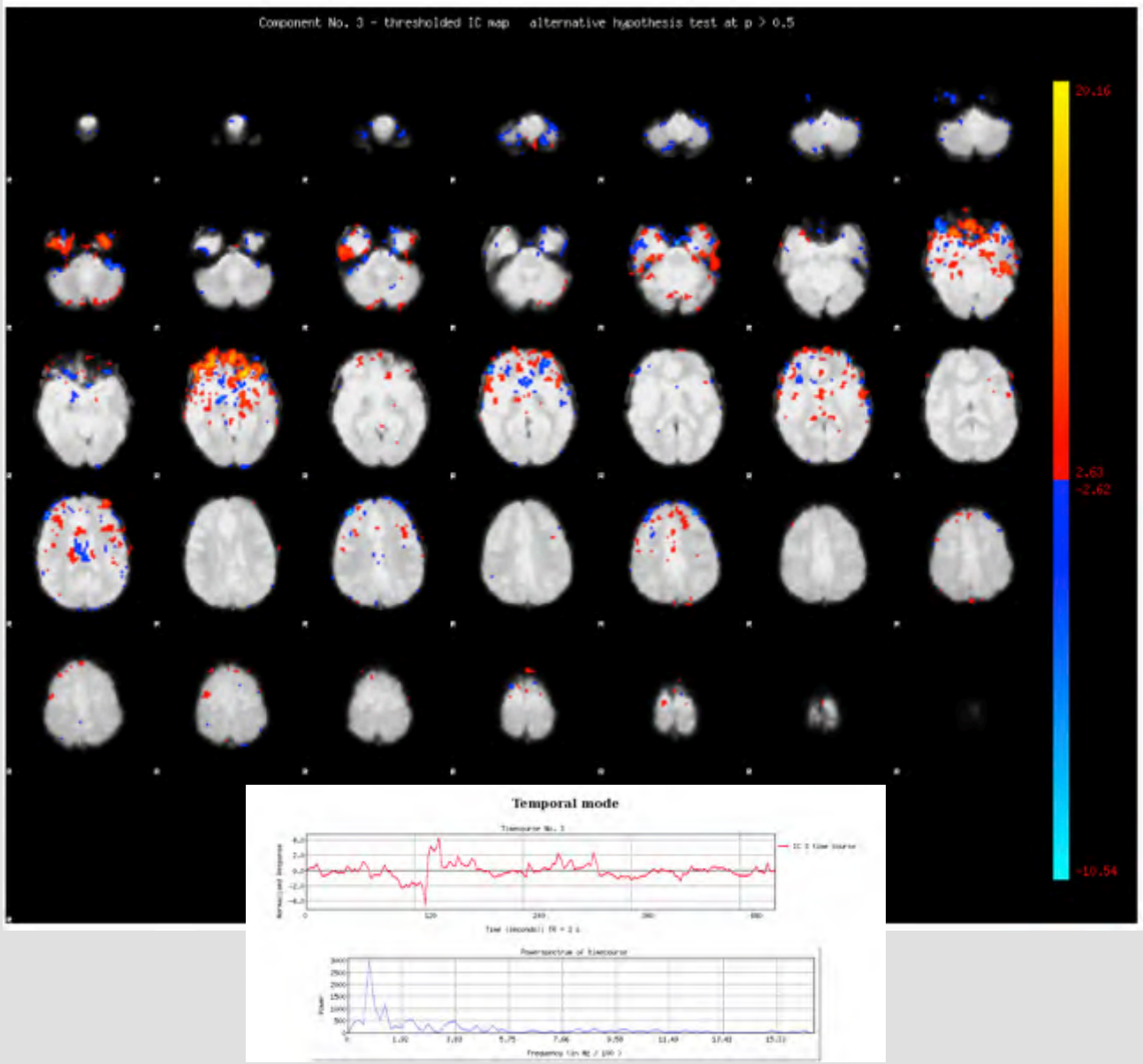
Generally due to head motion



Kelly et al.,2012 http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3299198/

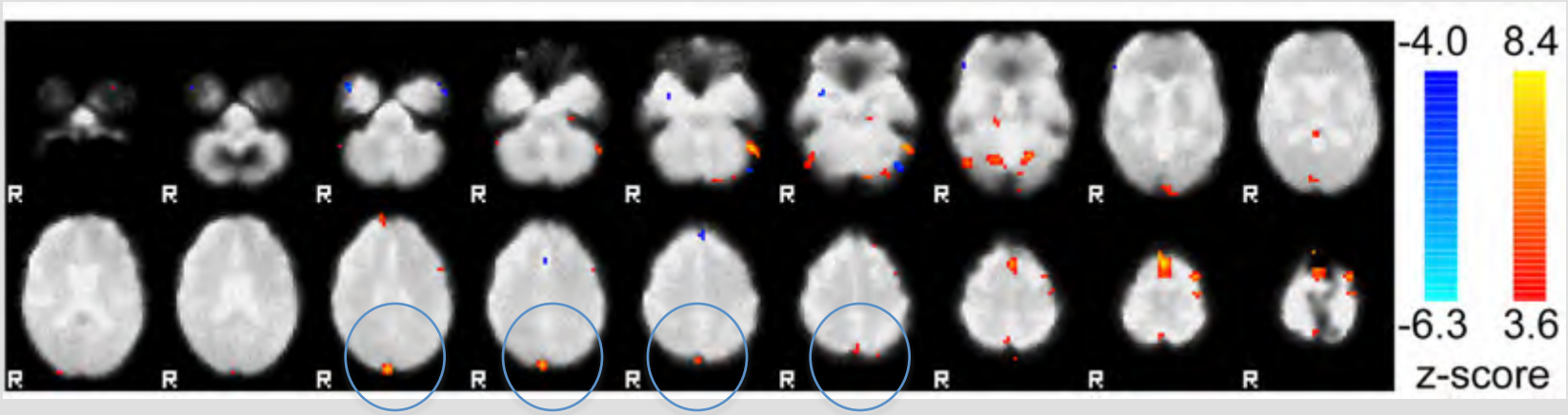
“Checkerboarding”

head motion along the z-axis

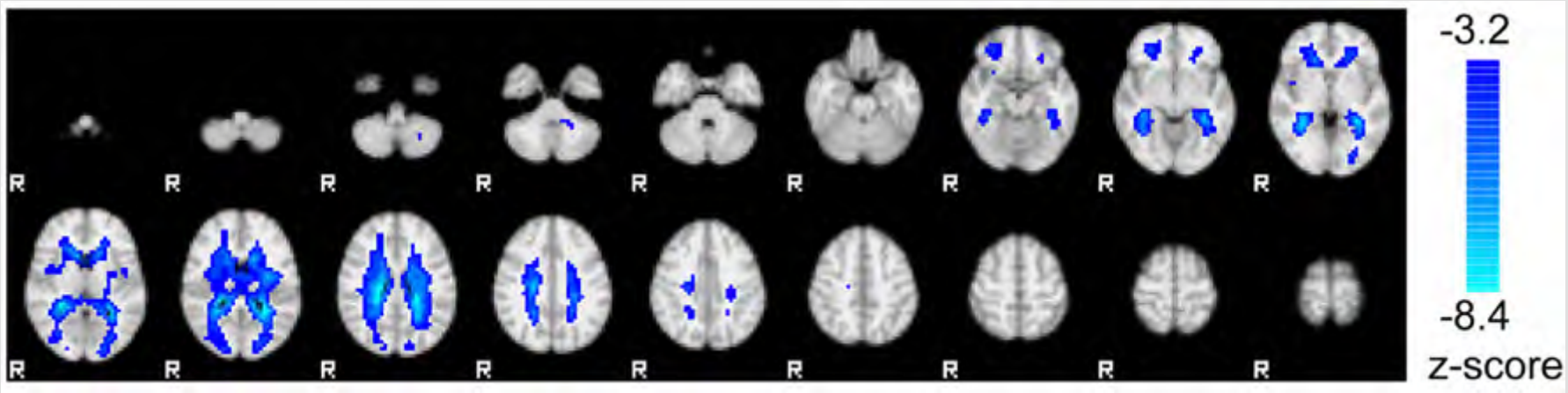


Posterior Sagittal Sinus

Artifact related to breathing and the cardiac cycle



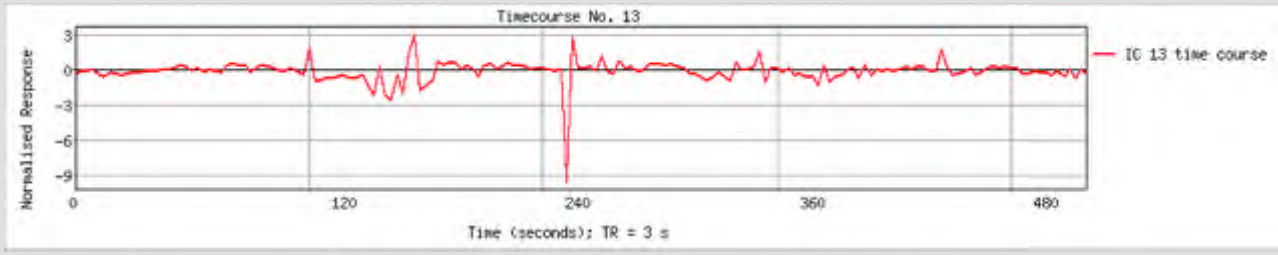
White Matter



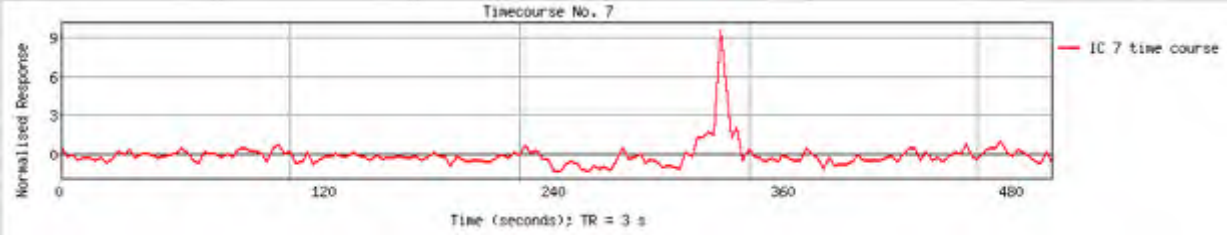
Kelly et al.,2012 http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3299198/

Time Courses

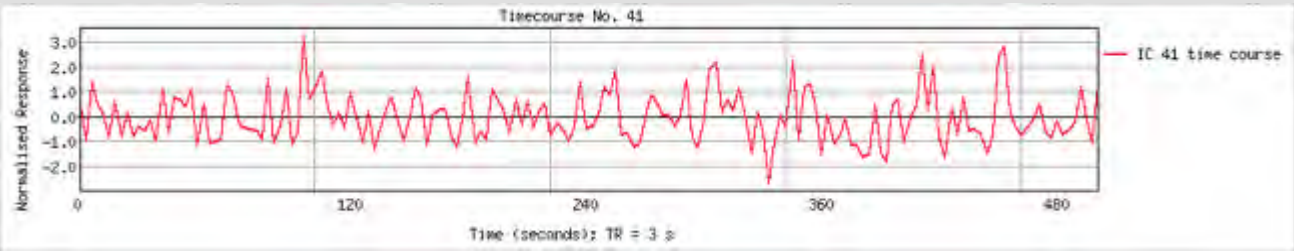
NOISE!



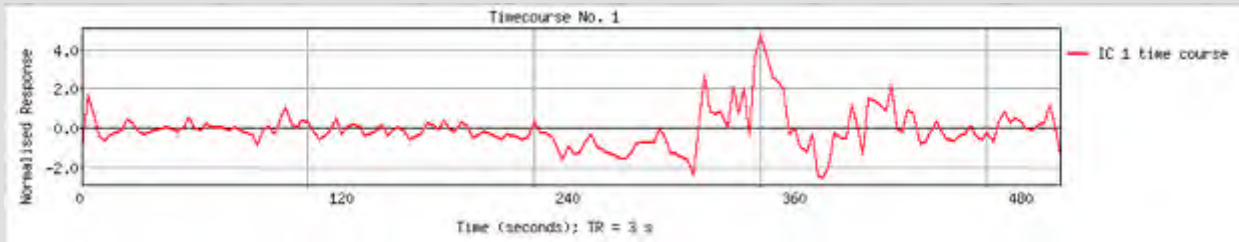
NOISE!



NOISE!

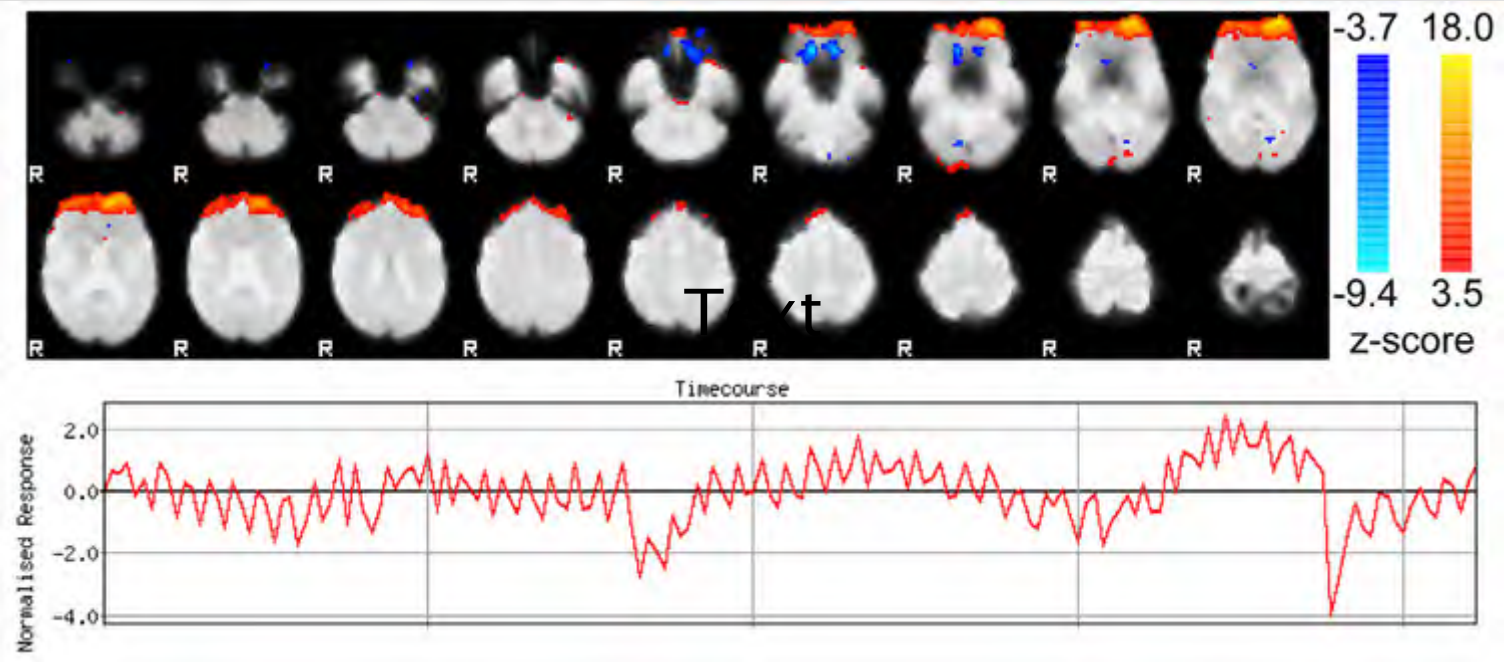


SIGNAL!



Saw-tooth pattern in time series

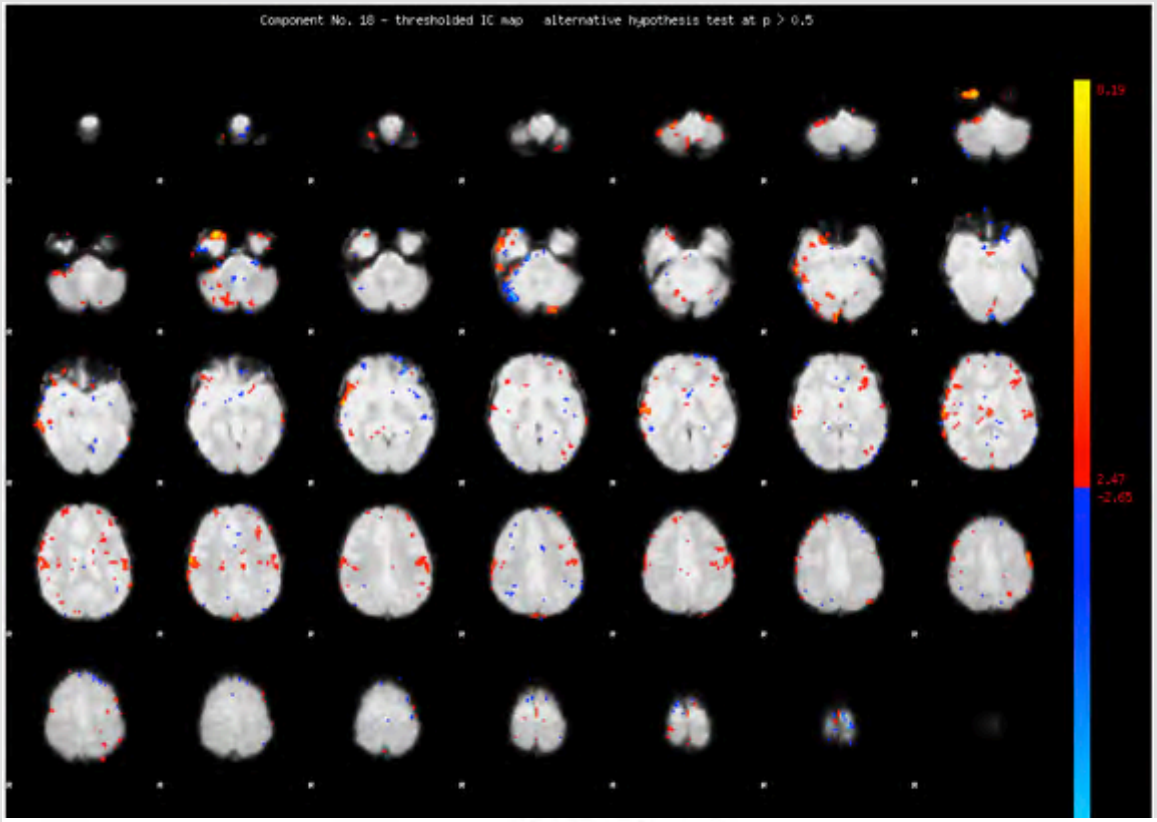
thought to be due to aliasing of cardiac or respiratory signals

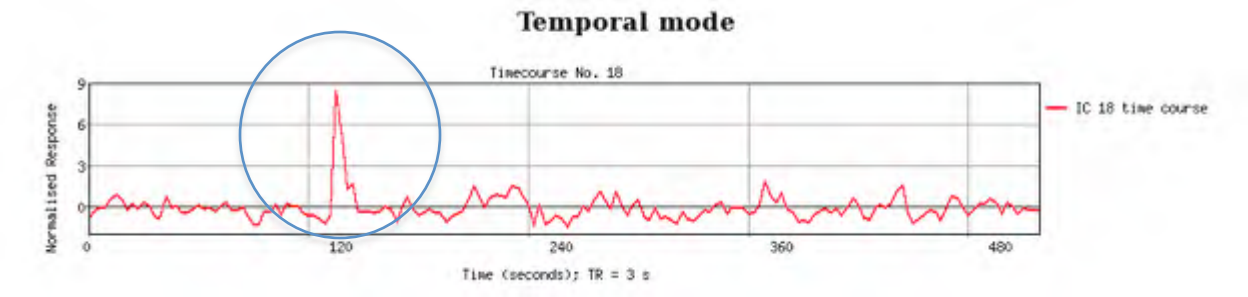


Kelly et al.,2012 http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3299198/

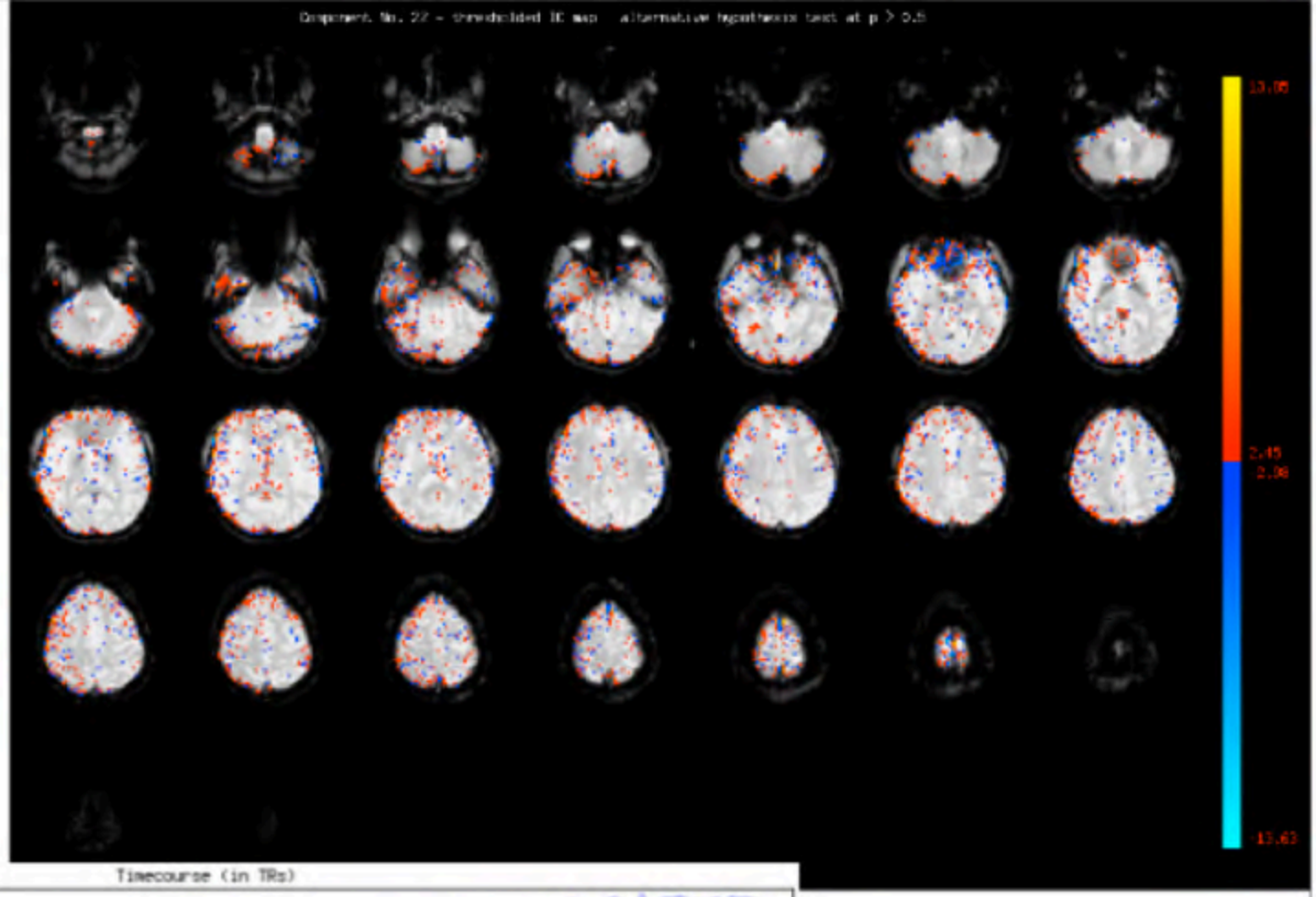
Large spikes (>5 SD's) in time series

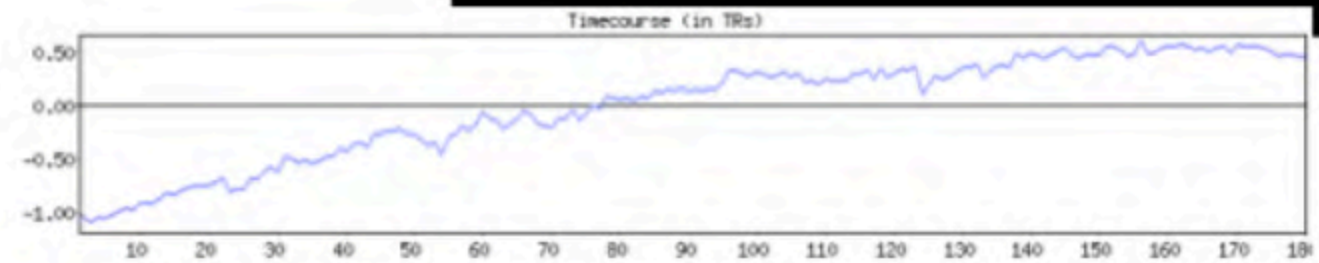
Generally due to head motion

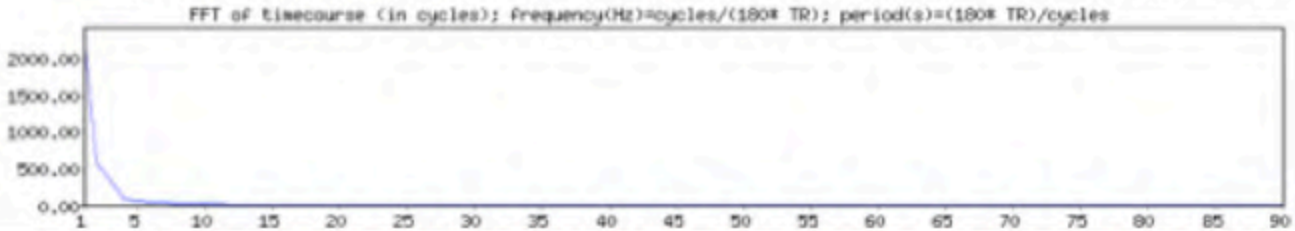




Slow drift

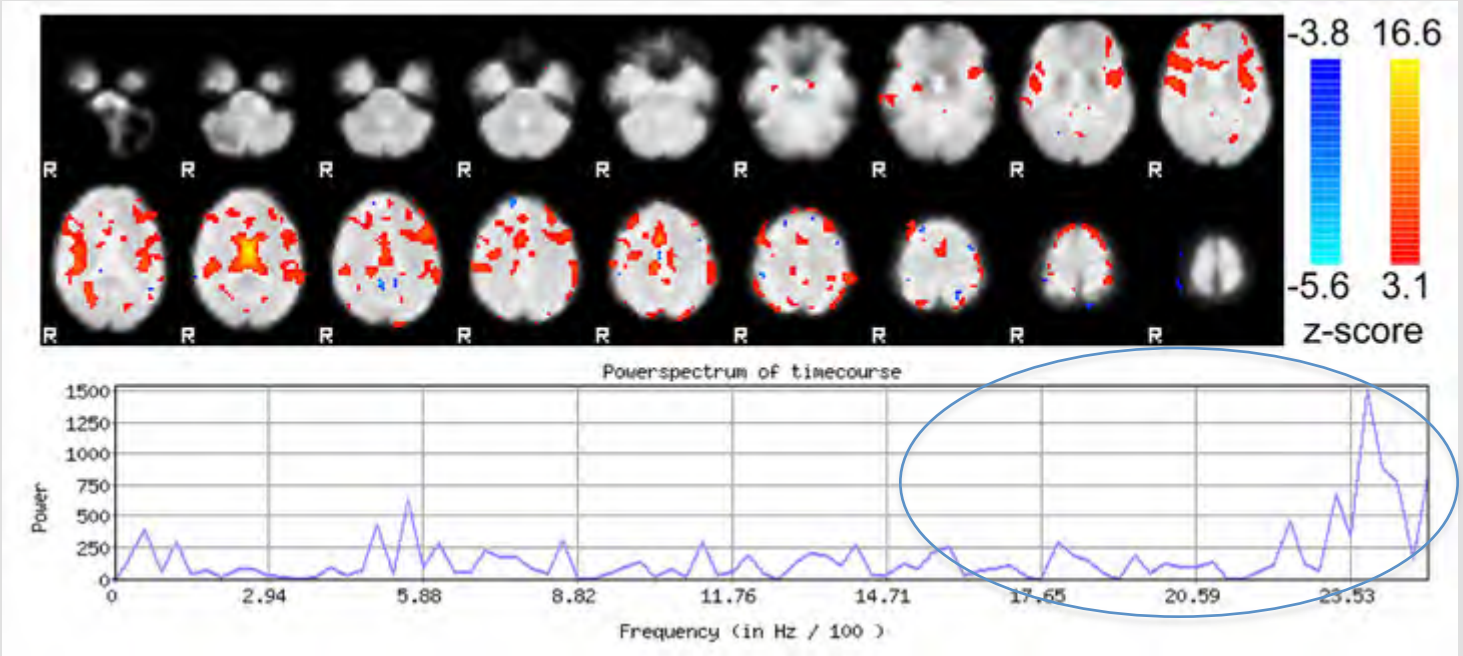






Source: R. Poldrack

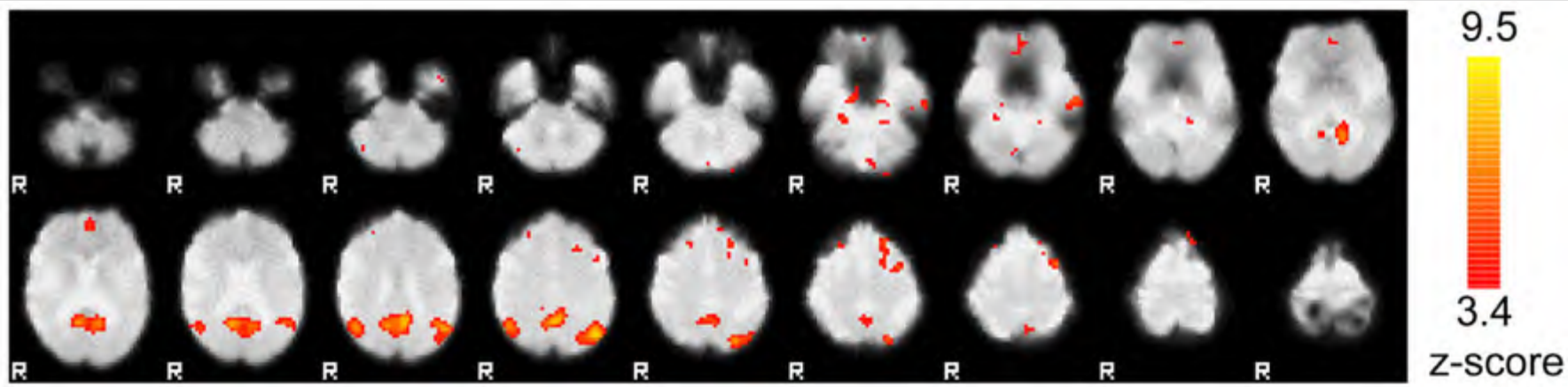
Power spectrum



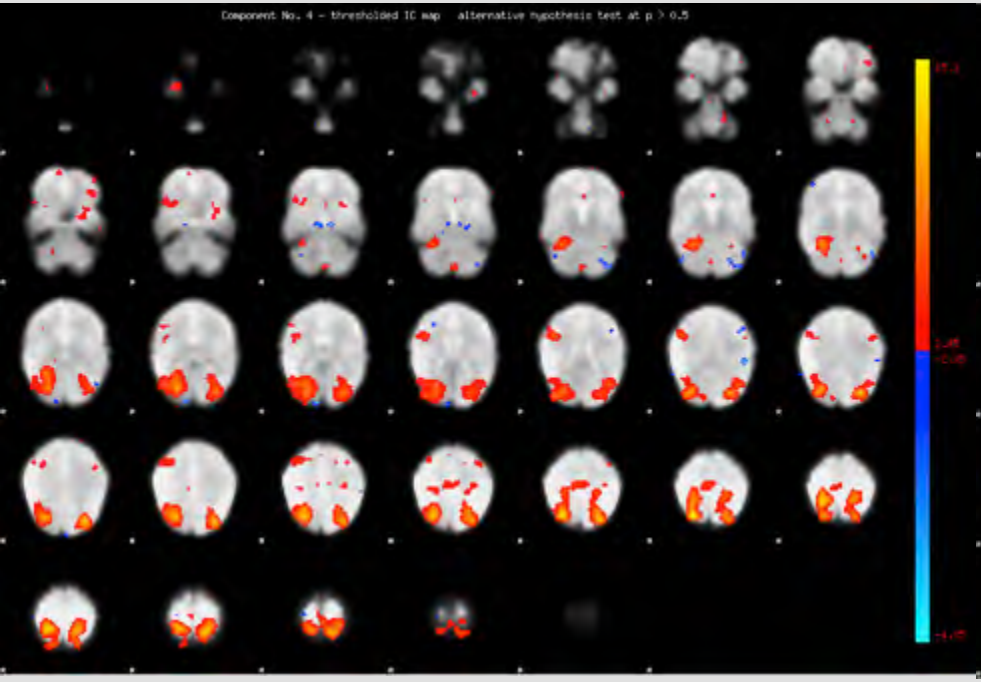
Kelly et al. (2012) recommend discarding components in which >50% of power lies at frequencies higher than 0.1Hz

R. Kelly et al.,2012

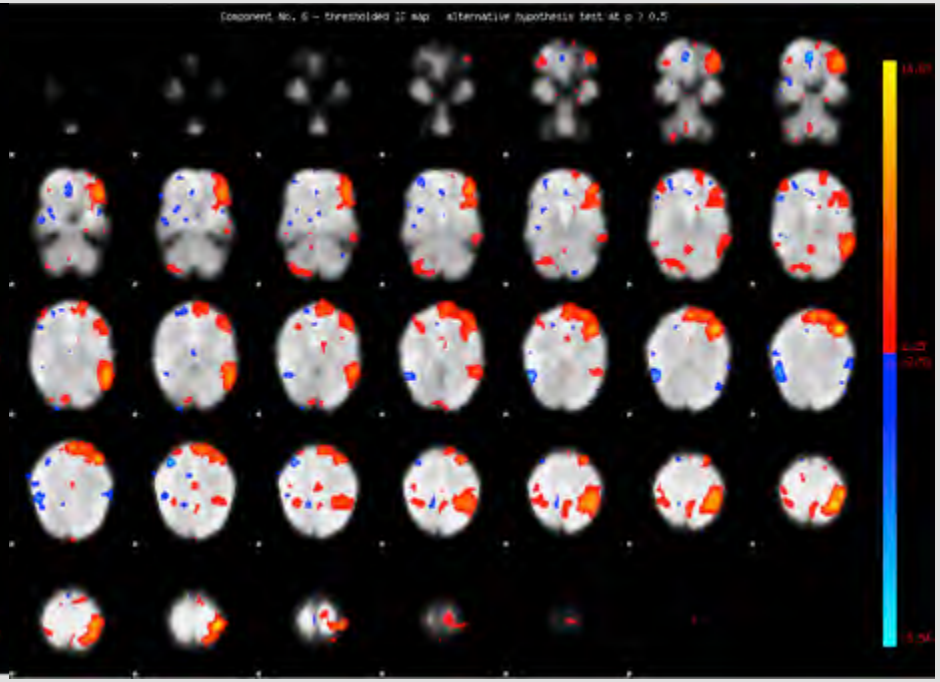
SIGNAL : Intrinsic Networks!



DMN

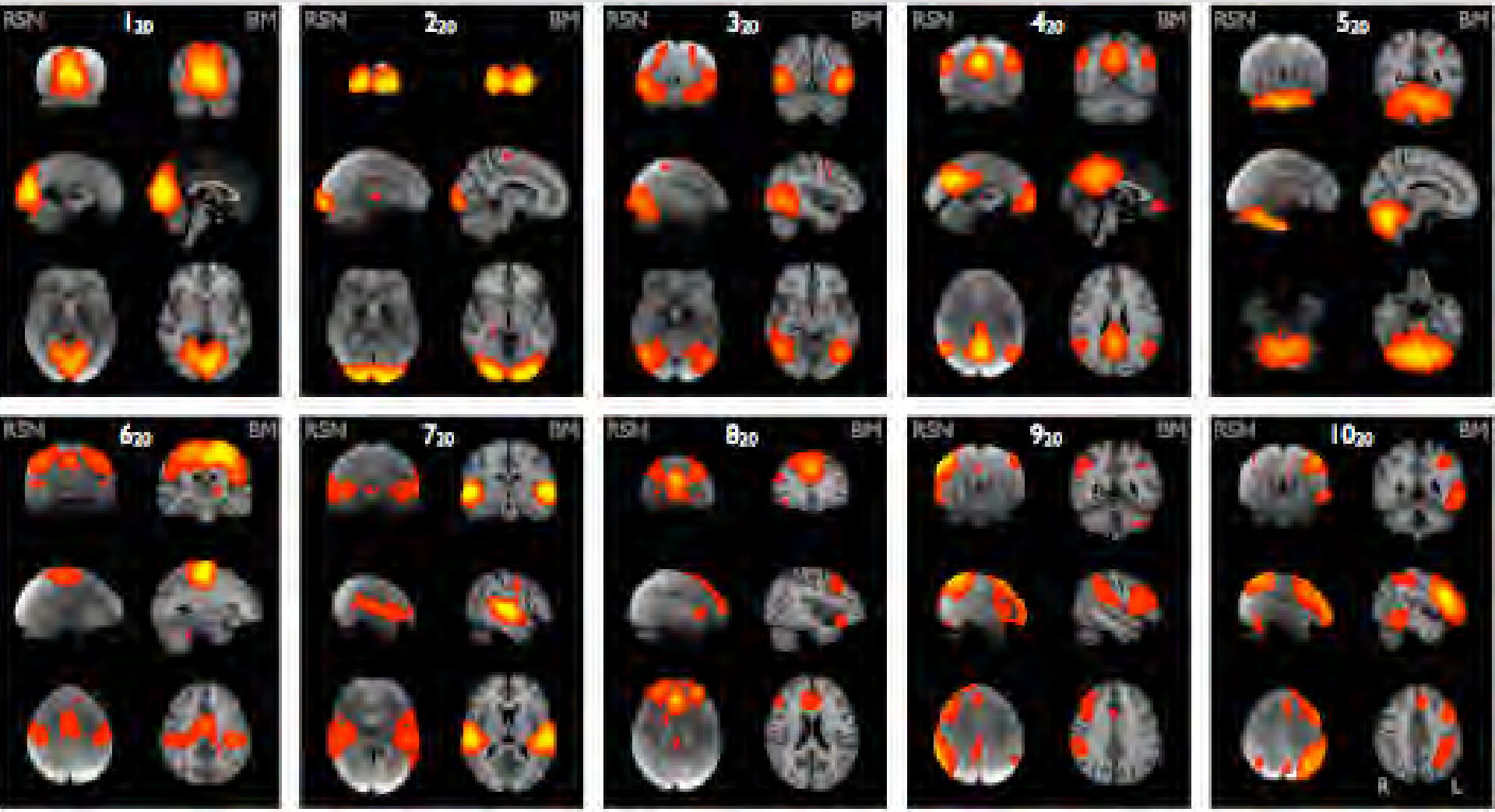


Secondary visual



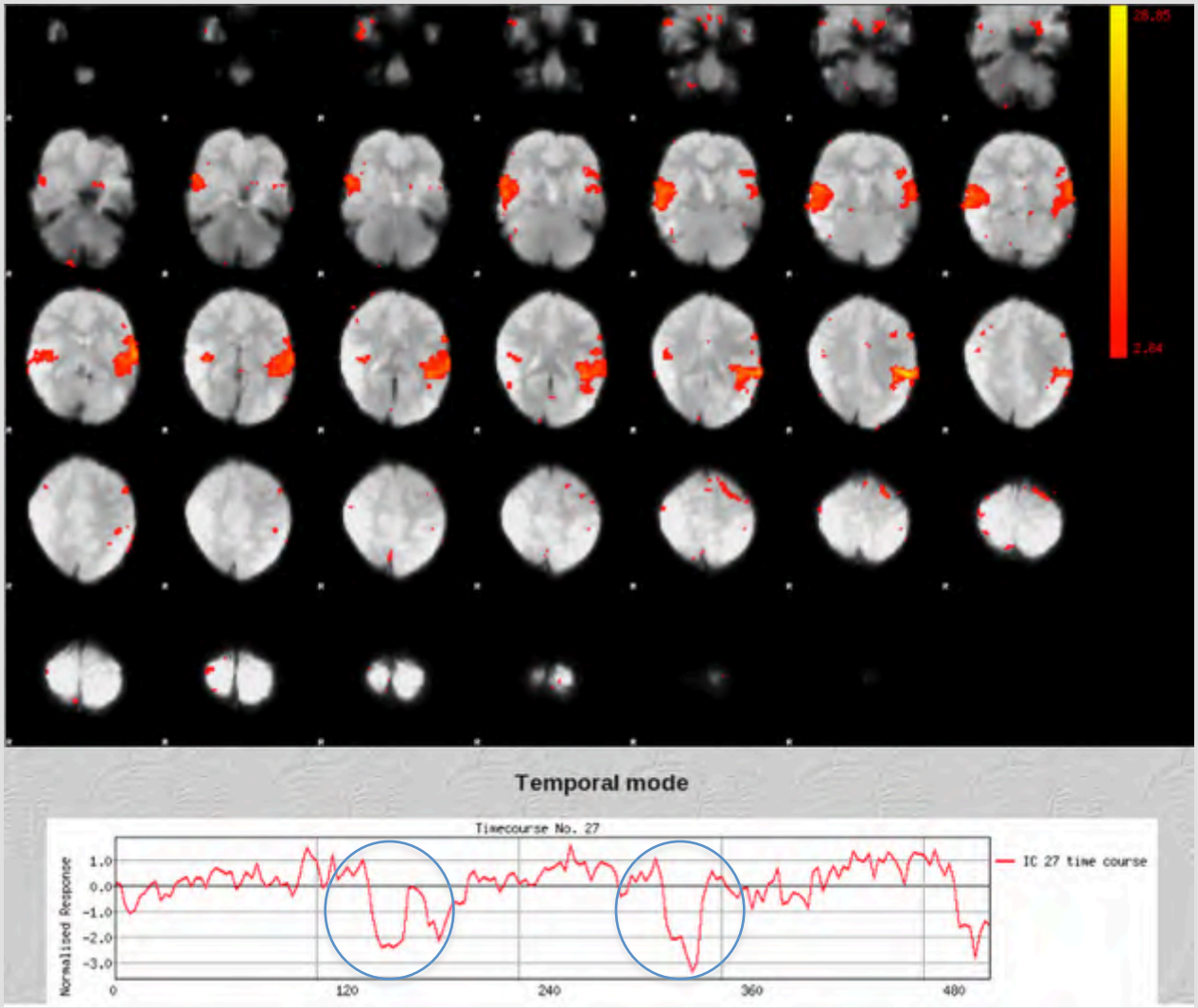
Left Lateralized task-positive

SIGNAL : Intrinsic Networks!



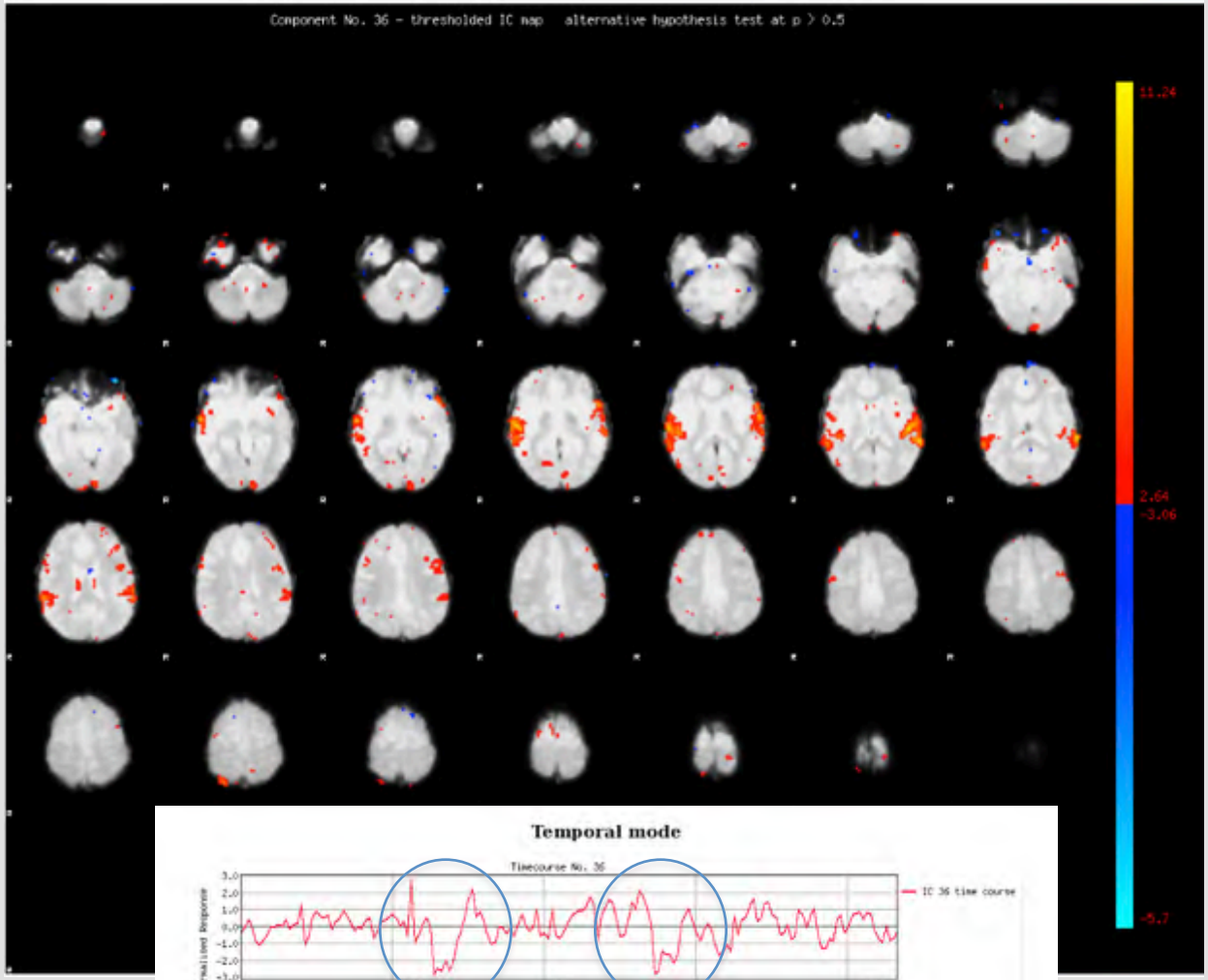
Smith et al., 2009 http://www.pnas.org/content/106/31/13040.long

SIGNAL : Task!

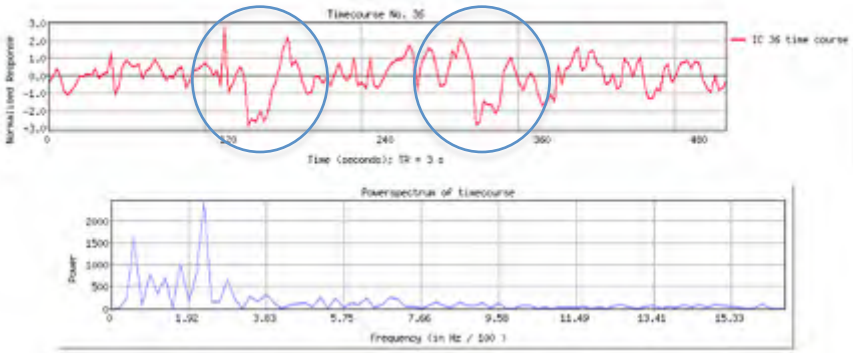

Temporal mode
Timecourse No. 27
Normalised Response
1.0
0.0
-1.0
-2.0
-3.0
0
120
240
360
480
IC 27 time course

MELODIC Component 36

1.89 % of explained variance; 1.28 % of total variance



Temporal mode



AND NOW…

WORKSHOP TIME!

But selecting ICs is boring, time-consuming, subjective, etc……..

Alternate solution is to develop algorithm to identify noise ICs based on priors (automation of what we do by eye)

All are variations on machine learning:
(Perlbarg 2007 CORSICA – physio; Sui et al 2009 – no time info;
De Martino et al 2007 – IC fingerprint; Tohka 2008 – ignores physio;
Bhaganagarapu 2013 – SOCK, didn't work)

But selecting ICs is boring, time-consuming, subjective, etc…….

A ithm
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Contents lists available at ScienceDirect

NeuroImage

journal homepage: www.elsevier.com/locate/ynimg

Automatic denoising of functional MRI data: Combining independent component analysis and hierarchical fusion of classifiers

Gholamreza Salimi-Khorshidi [a,*], Gwenaëlle Douaud [a], Christian F. Beckmann [b,c], Matthew F. Glasser [d], Ludovica Griffanti [a,e,f], Stephen M. Smith [a]

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[b] Donders Institute for Brain, Cognition and Behaviour, Radboud University, Nijmegen, The Netherlands
[c] MIRA Institute for Biomedical Technology and Technical Medicine, University of Twente, Enschede, The Netherlands
[d] Washington University School of Medicine, Washington University, St. Louis, MO, USA
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ABSTRACT

Many sources of fluctuation contribute to the fMRI signal, and this makes identifying the effects that are truly related to the underlying neuronal activity difficult. Independent component analysis (ICA) – one of the most widely used techniques for the exploratory analysis of fMRI data – has shown to be a powerful technique in iden-

Feature 1. Calculates many features – covering its basis.

Table 4
FIX's temporal features.

Index	Name & description
1	The number of independent components, as determined by MELODIC
2–3	The relationship between the order of the AR model and its goodness of fit
4–5	The parameter and the residual of AR(1)
6–8	The parameters and the residual of AR(2)
9:10	The skewness and kurtosis of the time series
11	The difference between timeseries mean and its median
12–13	Entropy (two different calculations)
14–19	Timeseries' jump characteristics
20–23	The ratio of the sum of power above fHz to the sum of power below fHz, for $f = 0.1, 0.15, 0.2$ and 0.25
24–30	Percent of total power that falls in 0:0.01, 0.01:0.025, 0.025:0.05, 0.05:0.1, 0.1:0.15, 0.15:0.2 and 0.2:0.25 Hz bins
31–38	Comparing the timeseries with their null model (i.e., convolving white noise with HRF)
30–44	Timeseries' correlation with motion timeseries and their derivatives
45–46	Timeseries' mean-reversion features

Table 5
FIX's spatial features.

Index	Name & description
47–55	Spatial maps' supra-threshold cluster-size distribution characteristics
56–61	The balance of negative and positive voxels in spatial maps
62–65	The ratio of the Z-stat to mean functional maps
66–69	Slice-wise statistics
70–73	Slice-groups' (e.g., slices with even or odd index) statistics
74–85	Spatial maps' overlap and correlation with GM, CSF and WM masks
86–87	Smoothness estimates
88–90	TFCE features
91–105	Edge-mask features
106–177	Sagittal sinus and veins mask-based features
178	Stripiness score/feature

Feature 2. Uses a hierarchical classifier (gives it a way of incorporating very different features to make a unitary decision about class)

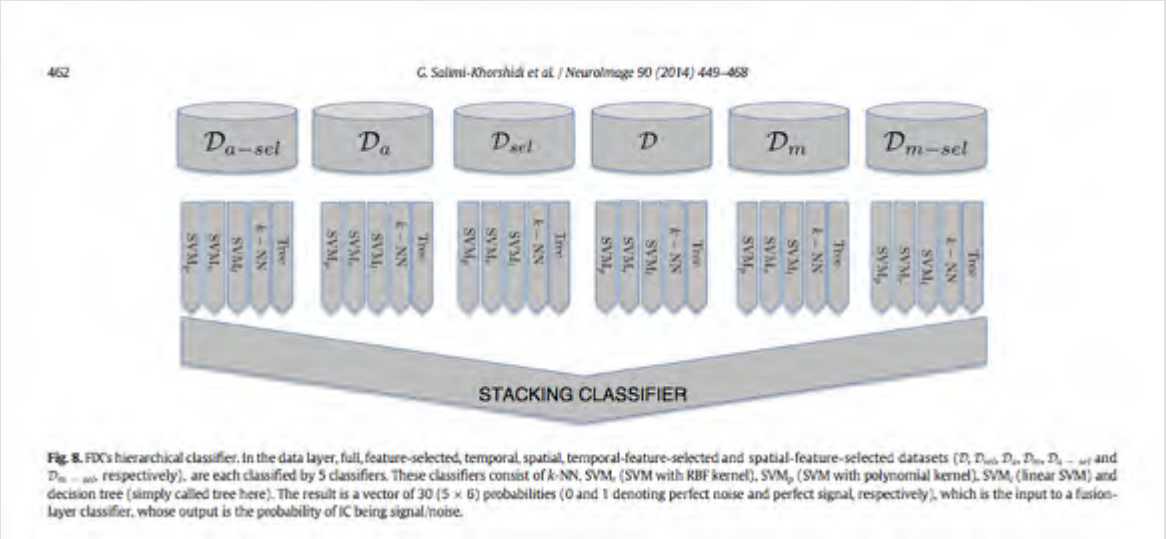

Fig. 8. FIX's hierarchical classifier. In the data layer, full, feature-selected, temporal, spatial, temporal-feature-selected and spatial-feature-selected datasets ($\mathcal{D}$, $\mathcal{D}_{sel}$, $\mathcal{D}_a$, $\mathcal{D}_m$, $\mathcal{D}_{a-sel}$ and $\mathcal{D}_{m-sel}$, respectively), are each classified by 5 classifiers. These classifiers consist of k-NN, SVM_r (SVM with RBF kernel), SVM_p (SVM with polynomial kernel), SVM_l (linear SVM) and decision tree (simply called tree here). The result is a vector of 30 (5 × 6) probabilities (0 and 1 denoting perfect noise and perfect signal, respectively), which is the input to a fusion-layer classifier, whose output is the probability of IC being signal/noise.

Steps to FIX:

1. “Train” classifier with hand labels (10 subs recommended) or use FSL’s templates
2. For candidate data, extract features and classify.
3. Remove bad ICs (same as before).

LAB: We’ve classified the ICs in Noisy.ica using the Standard.RData template. Your job is to inspect the output and evaluate FIX performane.