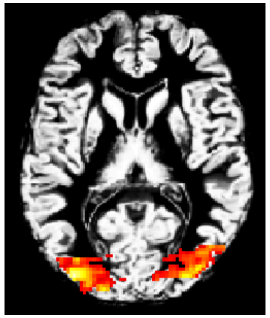

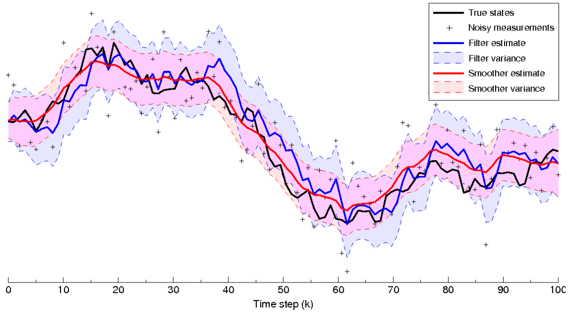

Dynamical statistical modeling of physiological noise for fast BOLD fMRI

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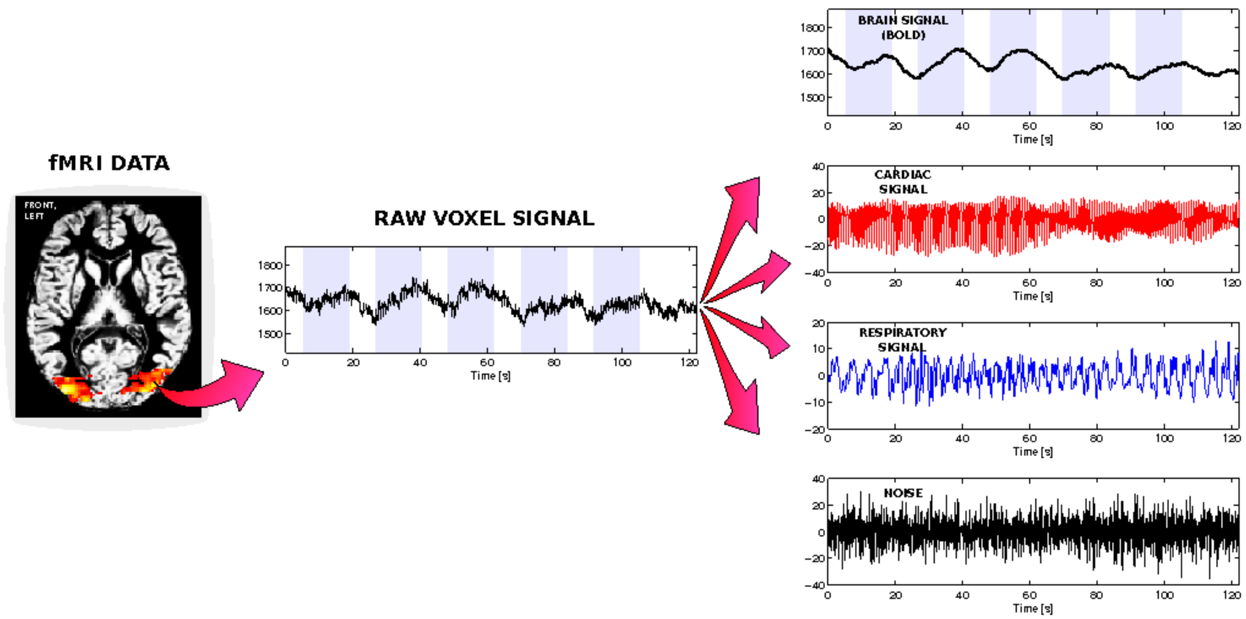
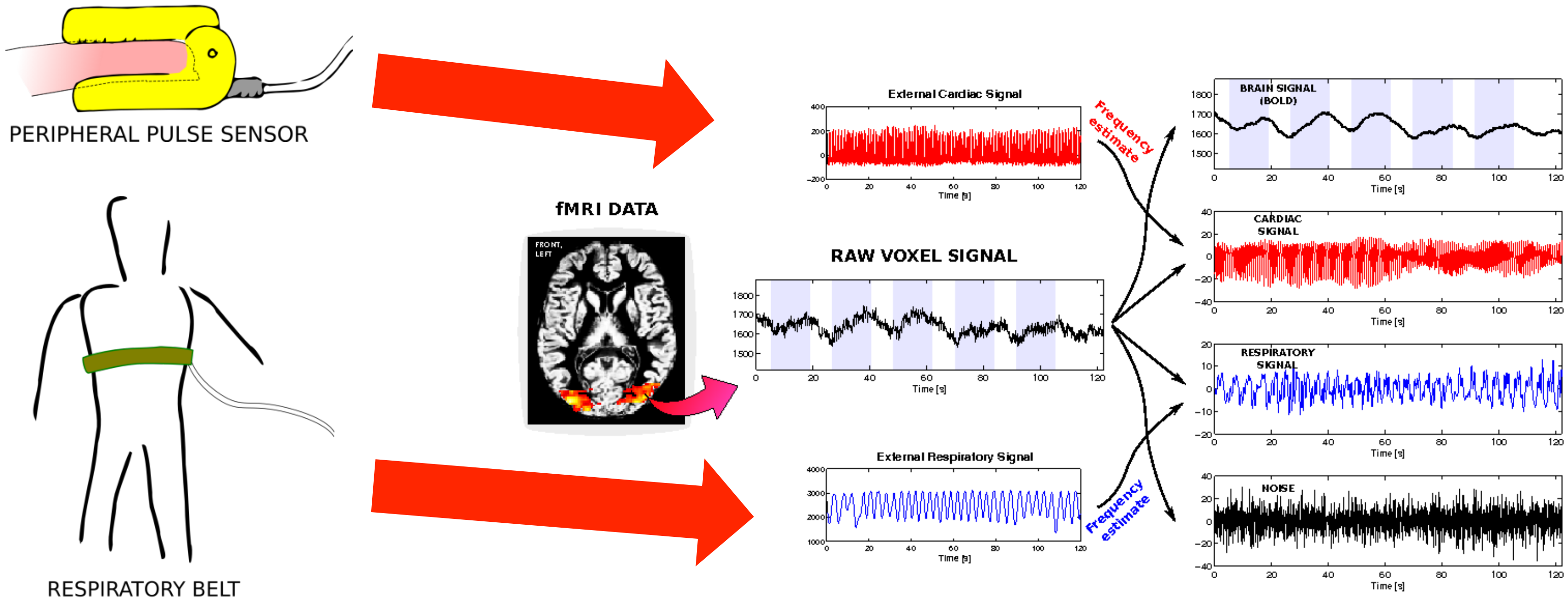
What we are aiming to do

- Eliminate cardiac and respiration (physiological signals) from fMRI measurements
- Separate signals to physiological and brain activation related components
- Bayesian stochastic dynamic model based approach
- Particularly well suited for fast fMRI (> 10Hz).



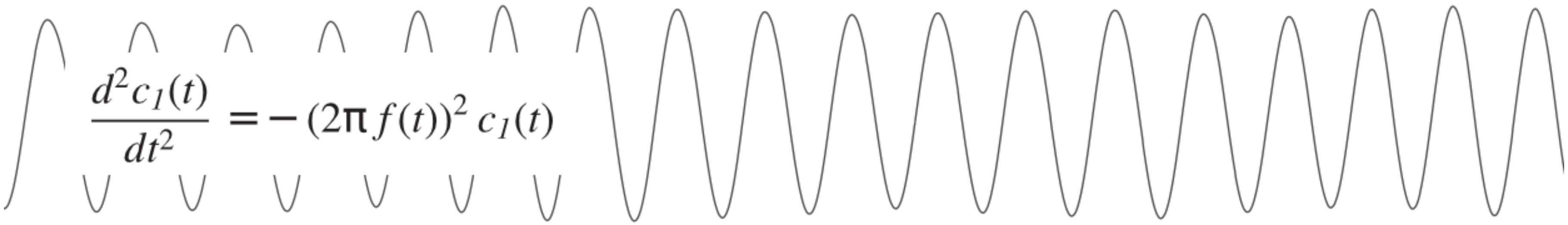
Utilization of reference signals

- Frequency trajectories of cardiac and respiration estimated from reference signals
- Used as the known oscillator frequencies in the Bayesian dynamic model of fMRI signal



Mathematical model for oscillator

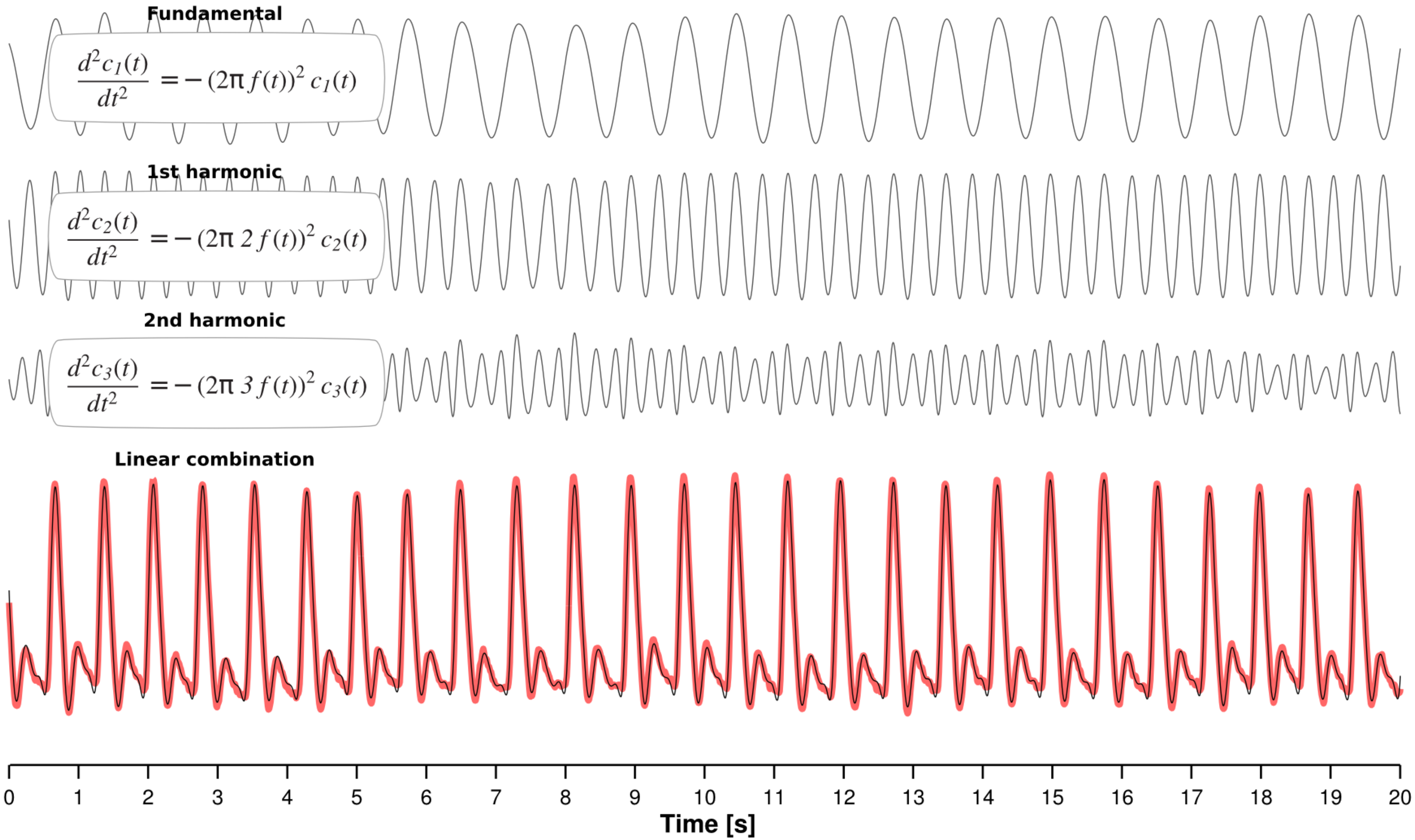
- Cardiac and respiration are modeled as superposition of oscillators c(t):



$$\frac{d^2 c_1(t)}{dt^2} = -\left(2\pi f(t)\right)^2 c_1(t)$$

- The frequency is assumed to be time-varying
- Frequency trajectories f(t) estimated from reference signals
- Uncertainties modeled with stochastic processes

Oscillator with Harmonics



Stochastic models for signals

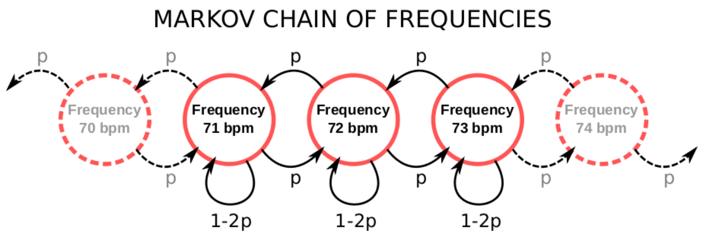
- Brain signal $b(t)$ in a voxel is modeled with Wiener velocity model, which contains white noise process $e_b(t)$:

$$\frac{d^2 b(t)}{dt^2} = e_b(t)$$

- The uncertainty in each harmonic oscillator $c_n(t)$ is modeled as white noise $e_n(t)$:

$$\frac{d^2 c_n(t)}{dt^2} = -(2\pi\, n\, f(t))^2\, c_n(t) + e_n(t)$$

- Frequencies $f(t)$ modeled as Hidden Markov Model (HMM):



State space model for references

- The models for reference signals can be written into state space model form

$$\frac{d\vec{x}_{rc}(t)}{dt} = F_{rc}(f_c(t))\,\vec{x}_{rc} + L_{rc}\,\vec{e}_{rc}$$

$$y_{rc}(t_k) = H_{rc}\,\vec{x}_{rc}(t_k) + v_{rc}, \qquad v_{rc} \sim \mathrm{N}(0, \sigma_{rc}^2),$$

- Here $y_{rc}(t_k)$ is the measured signal and $x_{rc}(t)$ is the state consisting of bias and oscillators:

$$\vec{x}_{rc} = \begin{pmatrix} b & db/dt & c_1 & dc_1/dt & \cdots & c_{N_{rc}} & dc_{N_{rc}}/dt \end{pmatrix}^T$$

- Bayesian solution with interacting multiple models (IMM) algorithm (a parallel set of Kalman filters)

State space model for brain signal

- Brain signal consists of spatio-temporal process defined in each voxel location *r*:

$$\frac{\partial \vec{x}(t, \vec{r})}{\partial t} = F\, \vec{x}(t, \vec{r}) + L\, \vec{e}(t, \vec{r})$$

$$y(t_k, \vec{r}) = H\, \vec{x}(t_k, \vec{r}) + v(\vec{r}),$$

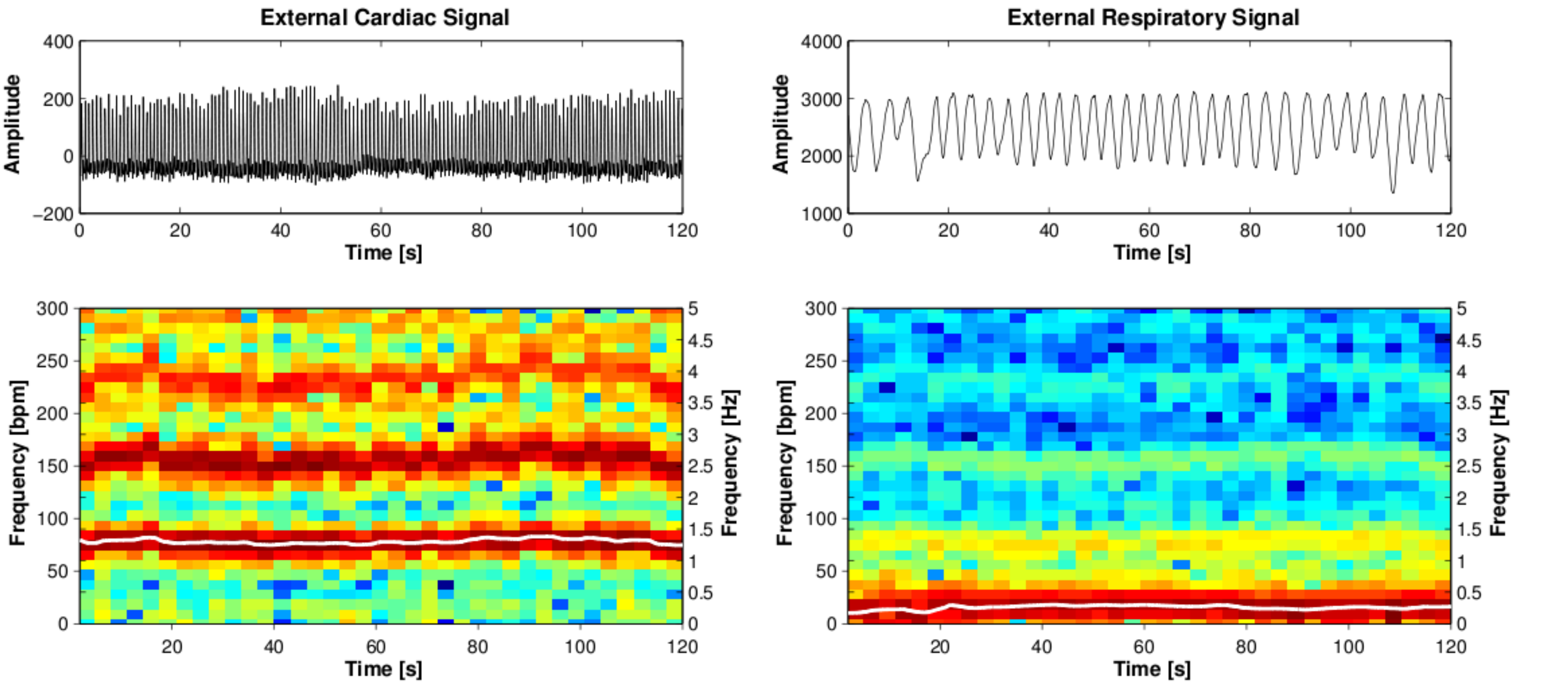
- The state $x(t,r)$ contains brain, cardiac and respiration signals in each voxel
- Bayesian solution can be computed with Kalman filter and RTS smoother
- Because voxels are treated independently, computations remain light

fMRI measurement setup

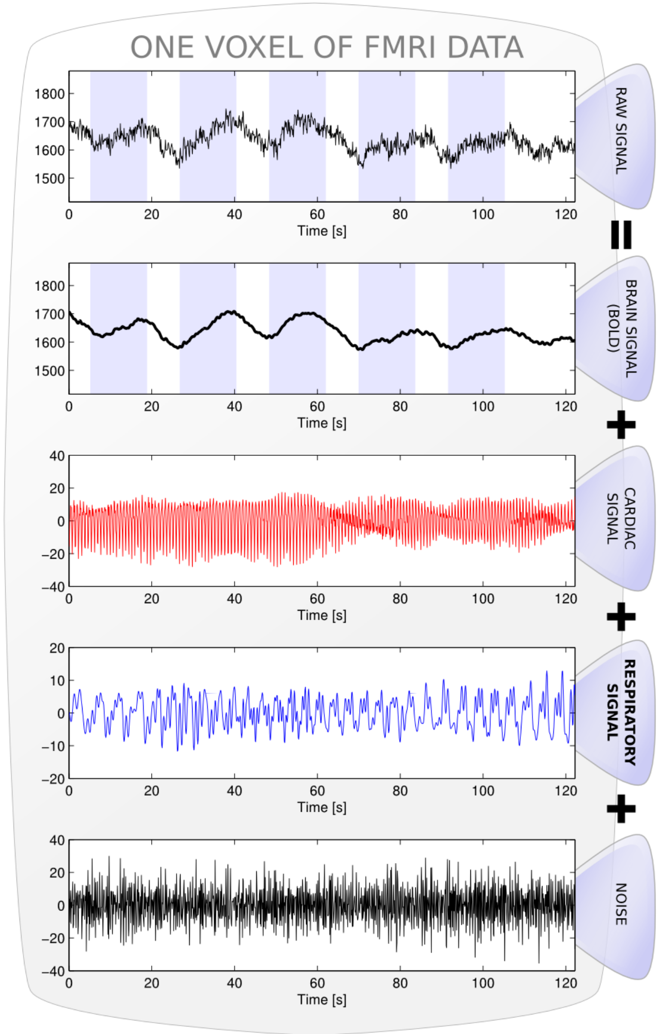
- Data was acquired with AMI-Centre's 3.0T scanner at Aalto University, Finland
- Stimuli consisted of photos in the center of the visual field in a block design
- Only 2 slices were measured with repetition time (TR), 100 ms; echo time (TE), 20 ms; flip angle (FA), 60; field-of-view (FOV), 20 cm; matrix size, 64x64; and slice thickness, 5 mm.
- During the EPI-runs, physiological signals were recorded at 1kHz.

Results: Analysis of reference signals

- Estimated frequency trajectories from the reference signals:

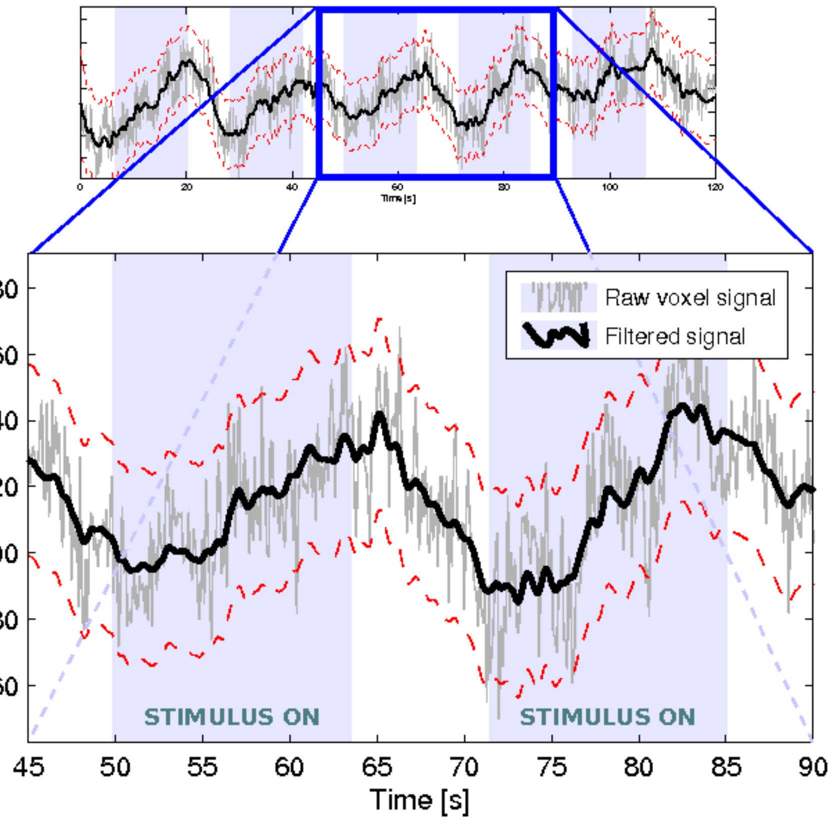


Results: Separation of signal into components



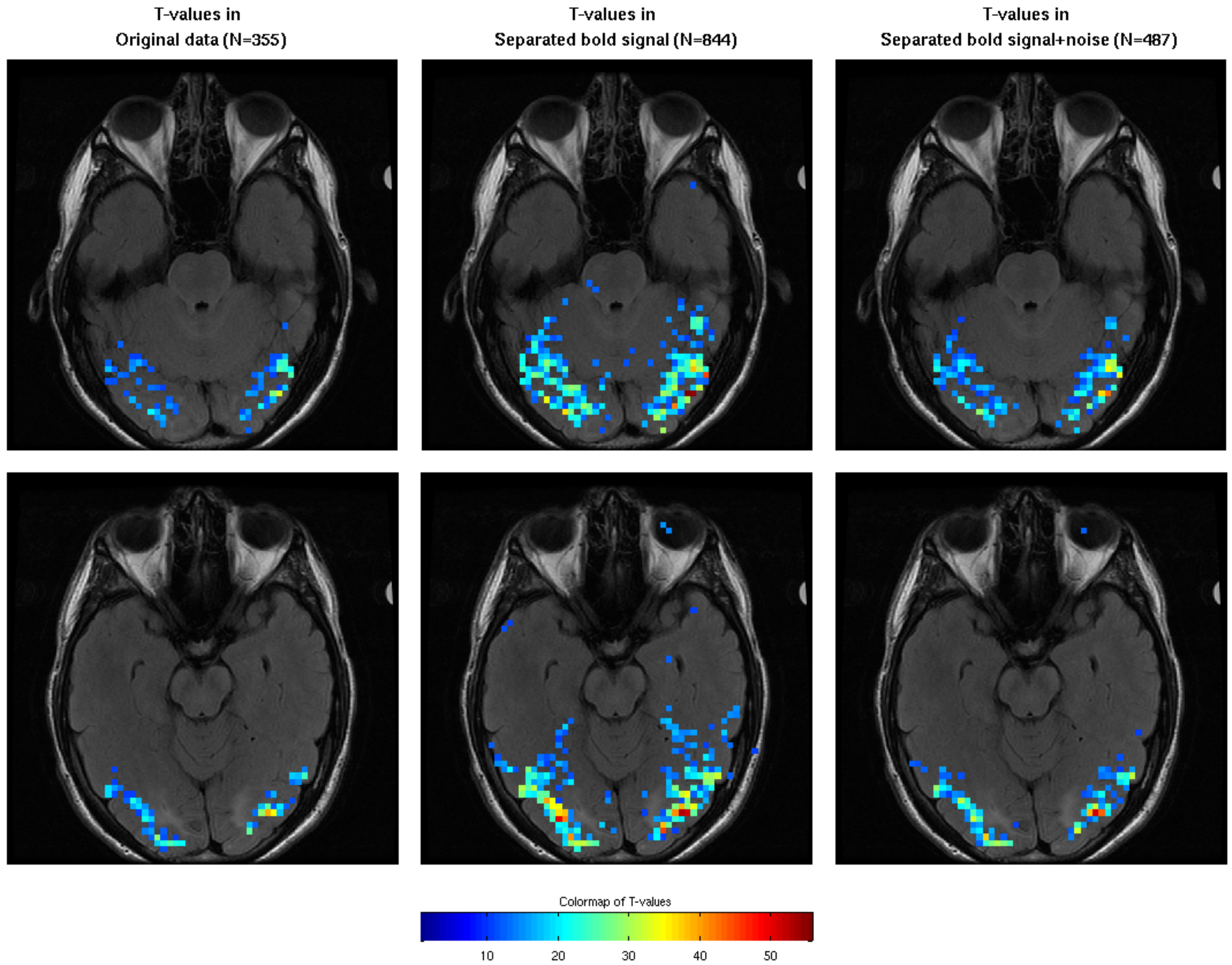
Results: Increase of SNR

- Removal of physiological and other noises improves the signal-to-noise-ratio (SNR):



Results: SPM results

Original signal | Physiological and other noises removed | Physiological noise removed



Summary

- We aim to eliminate physiological noise from fMRI by Bayesian stochastic dynamic modeling
- Frequency trajectories of cardiac and respiration are estimated from references with IMM algorithm
- Brain signal and physiological signals in brain are modeled with state space models and estimated with Kalman filter and RTS smoother
- The result is separation of fMRI signal into physiological, activation and noise components
- The separated activation signal has better SNR than the raw signal and results in better BOLD detection in SPM.
- Comparison to other approaches (RETROICOR) in progress
- Testing in normal ("slow") fMRI in progress