Inverse problems in functional brain imaging

Identification of the hemodynamic response in fMRI

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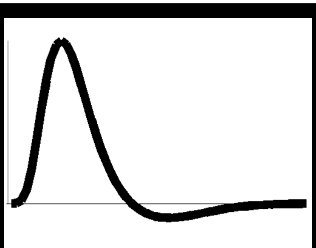
Brain dynamics in BOLD fMRI

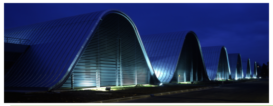
Probe brain dynamics non-invasively

stimulus → **hemodynamic response function (HRF)**



parametric HRF **[Friston et al, 1994; Glover et al, 1999]**
non-parametric HRF **[Goutte et al, 2000; Marrelec et al, 2003]**
non-stationary linear model **[Donnet et al, 2006]**
Balloon model **[Buxton et al, 1998; Friston, 2000; Buxton et al, 2004]**

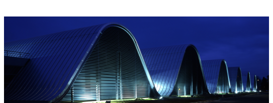
BOLD fMRI



Brain dynamics in fMRI

Why is it important?

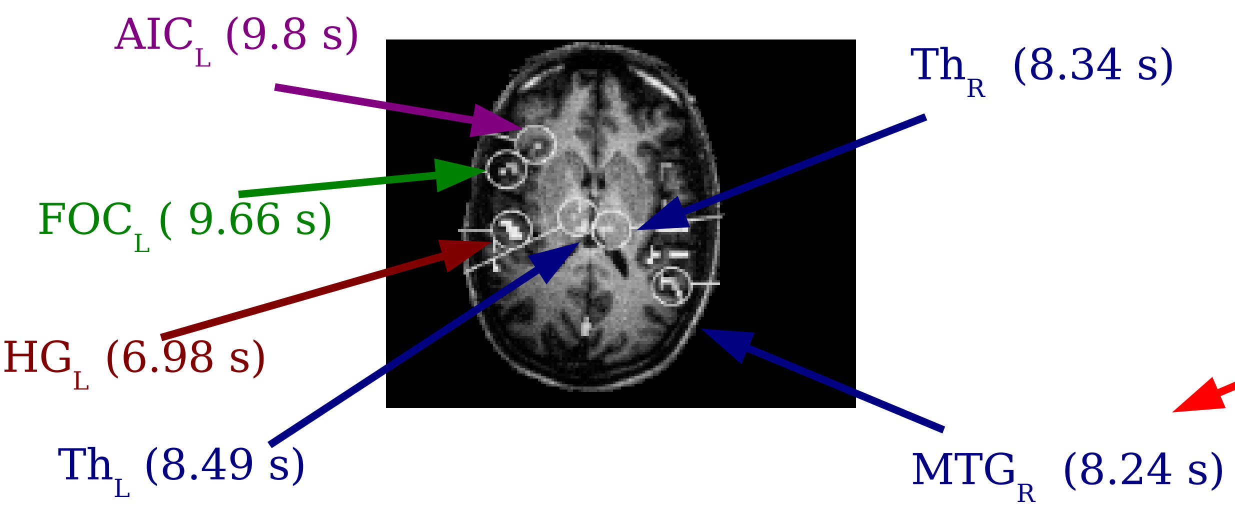
- Elucidate neural code:
  - Extract temporal information (magnitude, delay, width)
  - Study variability between conditions or tasks
  - Study non-linear or non-stationary effects
- Reflect subject's strategy or performance
  - Between subject variability
- Complementary analysis of electromagnetic modalities

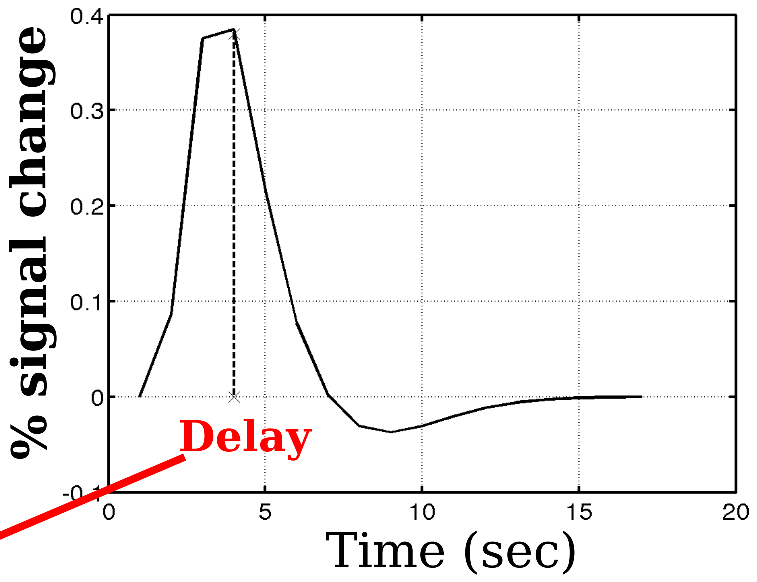


Extract temporal information

- Understanding the chronology of activations in single trial fMRI experiments
- Inferring the causality of underlying neural processes

[Kruggel & von Cramon, 1999]

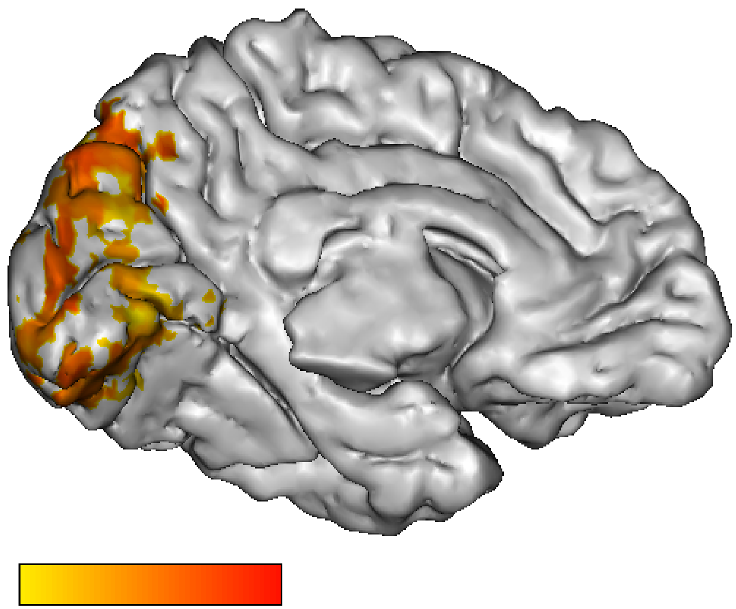


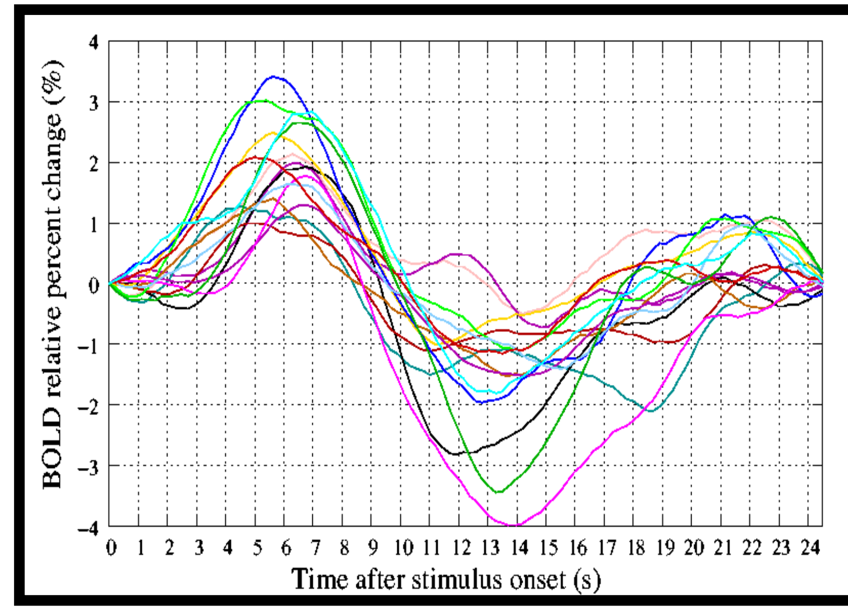


Delays (sec): $HG_L \sim HG_R < MTG_R \sim Th_R \sim Th_L < FOC_L$

[Saad et al 2001; Liao et al, 2002; Henson et al, 2002]

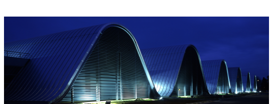
Delay mapping





Comparison of the HRF time to peak between voxels

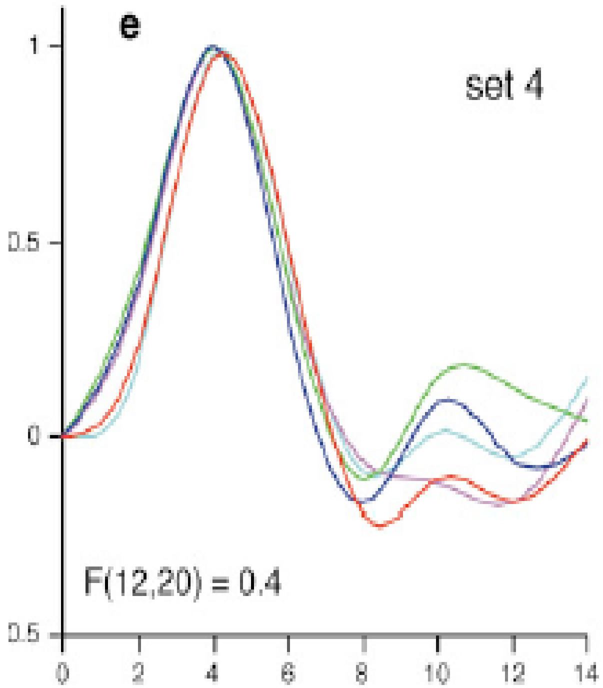
[Rabrait, Ciuciu et al, ISMRM '06]



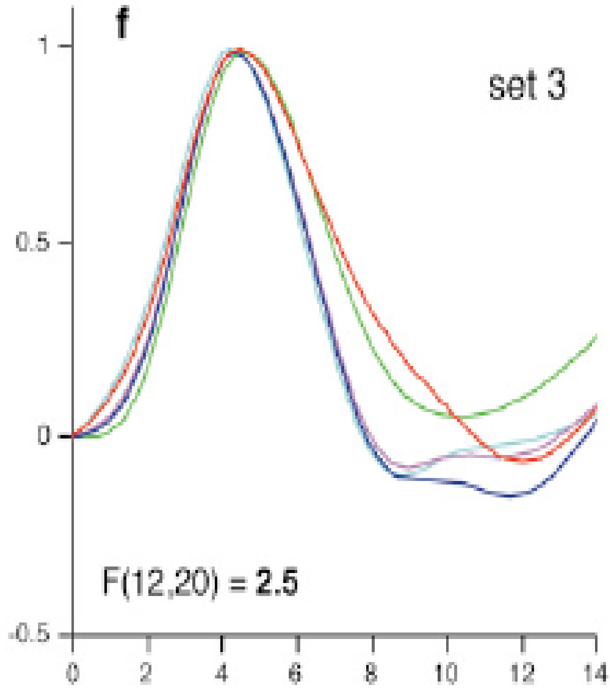
Sources of variability

- Subject, session

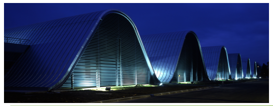
[Aguirre et al, NIM 1998]



Subject 1
less variable



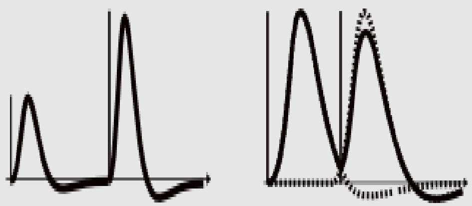
Subject 2
most variable



FIR modelling

- Explicit assumptions on the BOLD response

Hyp. 1: **linearity**



\+

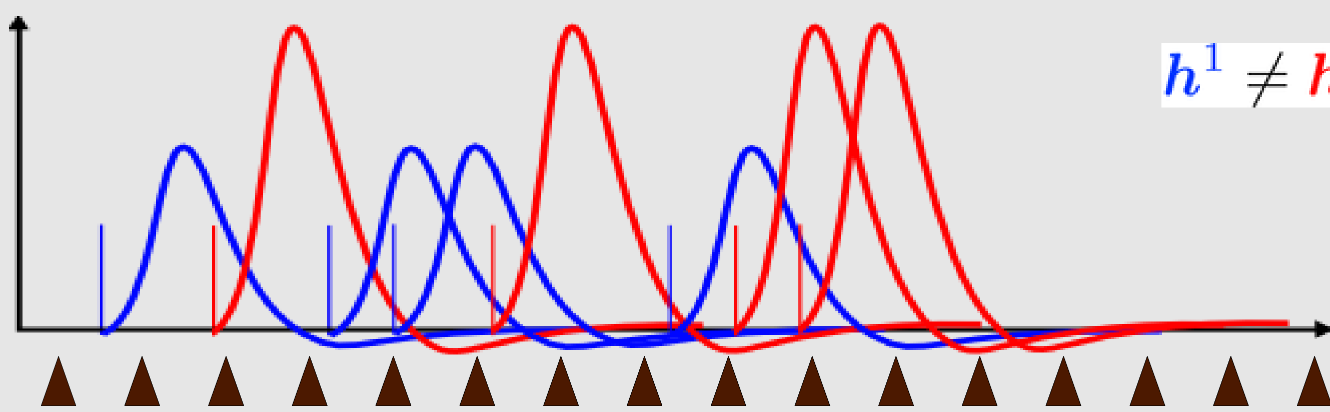
Hyp 2: **stationarity**

$\boldsymbol{h}$

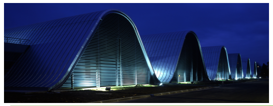
Convolution kernel

[Aguirre et al, 1998; McGonigle et al, 2000; Smith et al, 2005]

Hyp 3: **additivity**



[Ciuciu et al, 2003; Makni et al, 2008]



FIR modelling

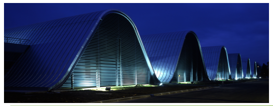
- Design matrix for estimating the evoked BOLD response

$$\begin{bmatrix} y_j(t_1) \\ y_j(t_2) \\ y_j(t_3) \\ y_j(t_4) \\ y_j(t_5) \\ \vdots \\ \vdots \\ y_j(t_9) \\ y_j(t_{10}) \\ y_j(t_{11}) \\ y_j(t_{12}) \\ y_j(t_{13}) \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} h_j^1(0) \\ h_j^1(\Delta t) \\ \vdots \\ h_j^1(4\Delta t) \\ h_j^2(0) \\ h_j^2(\Delta t) \\ \vdots \\ h_j^2(4\Delta t) \\ m_j \end{bmatrix} + \begin{bmatrix} \varepsilon_j(t_1) \\ \varepsilon_j(t_2) \\ \varepsilon_j(t_3) \\ \varepsilon_j(t_4) \\ \varepsilon_j(t_5) \\ \vdots \\ \vdots \\ \varepsilon_j(t_9) \\ \varepsilon_j(t_{10}) \\ \varepsilon_j(t_{11}) \\ \varepsilon_j(t_{12}) \\ \varepsilon_j(t_{13}) \end{bmatrix}$$

$(\Delta t = \mathrm{TR})$

$$\boldsymbol{y}_j = [\boldsymbol{X}^1 \,|\, \boldsymbol{X}^2 \,|\, \mathbf{1}] \begin{bmatrix} \boldsymbol{h}_j^1 \\ \boldsymbol{h}_j^2 \\ m_j \end{bmatrix} + \boldsymbol{\varepsilon}_j$$

$$= \sum_{m=1}^{M} \boldsymbol{X}^m \boldsymbol{h}^m + m_j \mathbf{1} + \boldsymbol{\varepsilon}_j$$



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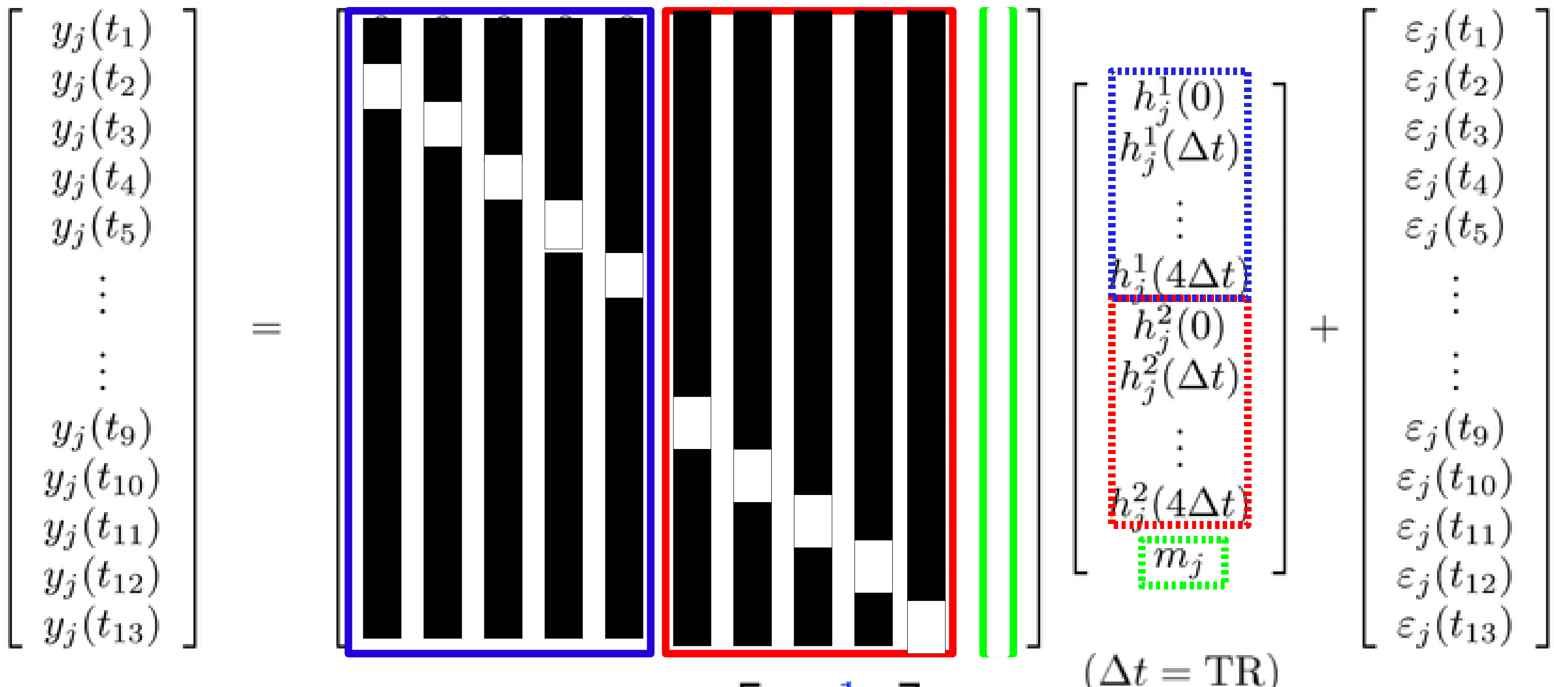

$$\boldsymbol{y}_j = \left[\boldsymbol{X}^1 \mid \boldsymbol{X}^2 \mid \mathbf{1}\right] \begin{bmatrix} \boldsymbol{h}_j^1 \\ \boldsymbol{h}_j^2 \\ m_j \end{bmatrix} + \boldsymbol{\varepsilon}_j$$

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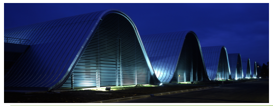


FIR fitting procedure

- Least squares solution (white Gaussian noise)

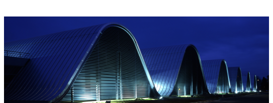
$$\begin{bmatrix} \widehat{\boldsymbol{h}}_j^{\,\mathrm{OLS}} \\ \widehat{m}_j^{\,\mathrm{OLS}} \end{bmatrix} = \left(\mathbb{X}^{\mathrm{t}}\mathbb{X}\right)^{-1}\mathbb{X}^{\mathrm{t}}\boldsymbol{y}_j$$

$$\text{with } \mathbb{X} = \left[\boldsymbol{X}^1 \,|\, \boldsymbol{X}^2 \,|\, \mathbf{1}\right]$$

- Maximum likelihood solution:
  - Noise structure modelling & estimation

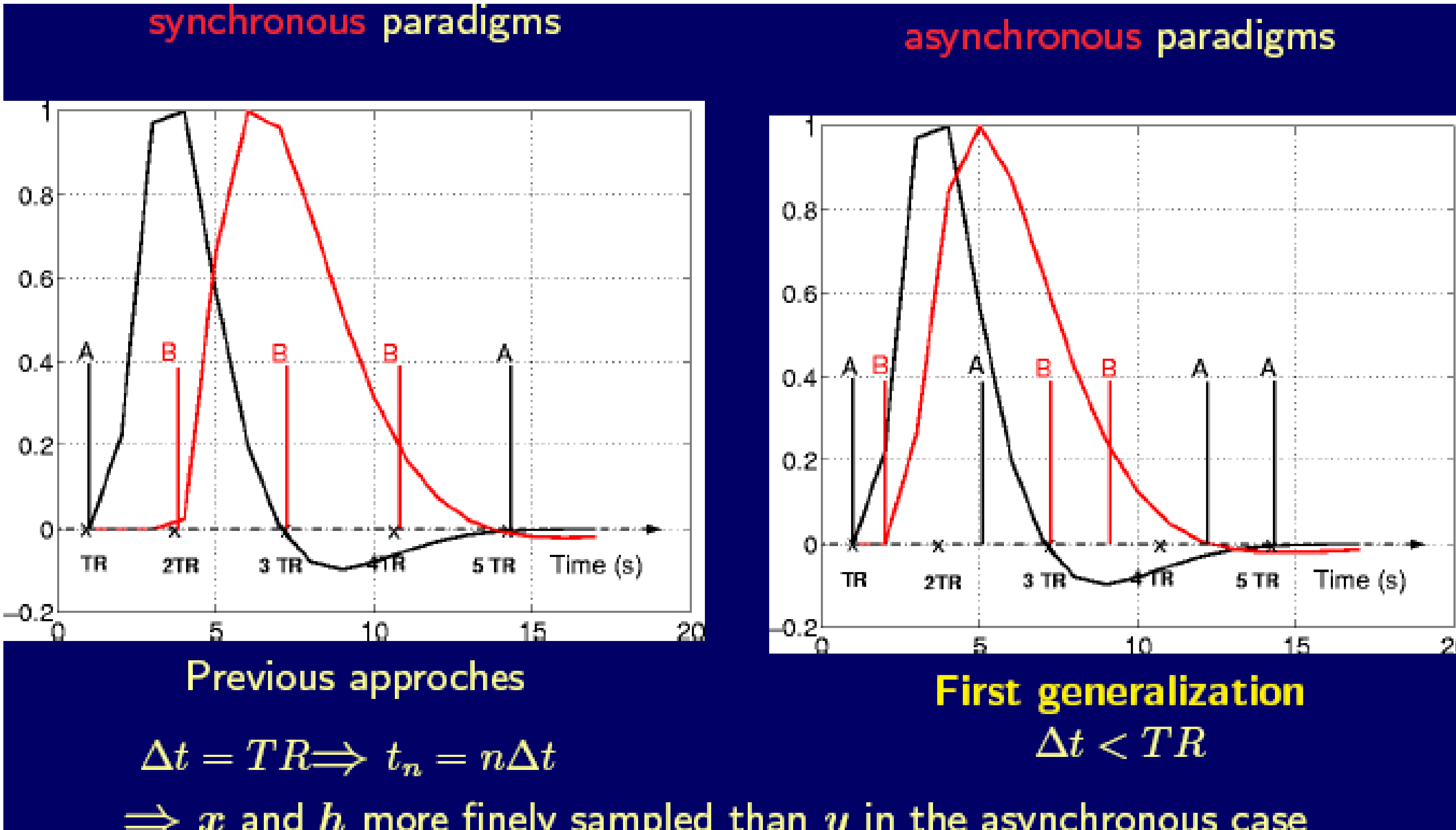
$$\begin{bmatrix} \widehat{\boldsymbol{h}}_j^{\,\mathrm{ML}} \\ \widehat{m}_j^{\,\mathrm{ML}} \end{bmatrix} = \left(\mathbb{X}^{\mathrm{t}}\Sigma_j^{-1}\mathbb{X}\right)^{-1}\mathbb{X}^{\mathrm{t}}\Sigma_j^{-1}\boldsymbol{y}_j$$

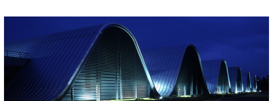
$$\text{with } \mathbb{X} = \left[\boldsymbol{X}^1 \,|\, \boldsymbol{X}^2 \,|\, \mathbf{1}\right]$$



Actual fMRI experiments

- “Asynchronous” paradigms (jittering)





over-sampled FIR model

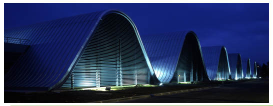
- Design matrix for estimating a single HRF
  - 3 events

$$
\begin{bmatrix} y_j(t_1) \\ y_j(t_2) \\ y_j(t_3) \\ \vdots \\ \vdots \\ \vdots \\ y_j(t_{11}) \\ y_j(t_{14}) \\ y_j(t_{15}) \end{bmatrix}
=
\begin{bmatrix}
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\
1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1
\end{bmatrix}
\begin{bmatrix} h_j^1(0) \\ h_j^1(\Delta t) \\ h_j^1(4\Delta t) \\ \vdots \\ \vdots \\ h_j^1(7\Delta t) \\ h_j^1(8\Delta t) \\ h_j^1(9\Delta t) \\ m_j \end{bmatrix}
+
\begin{bmatrix} \varepsilon_j(t_1) \\ \varepsilon_j(t_2) \\ \varepsilon_j(t_3) \\ \vdots \\ \vdots \\ \vdots \\ \varepsilon_j(t_{11}) \\ \varepsilon_j(t_{14}) \\ \varepsilon_j(t_{15}) \end{bmatrix}
$$

$$(\Delta t < \mathrm{TR})$$

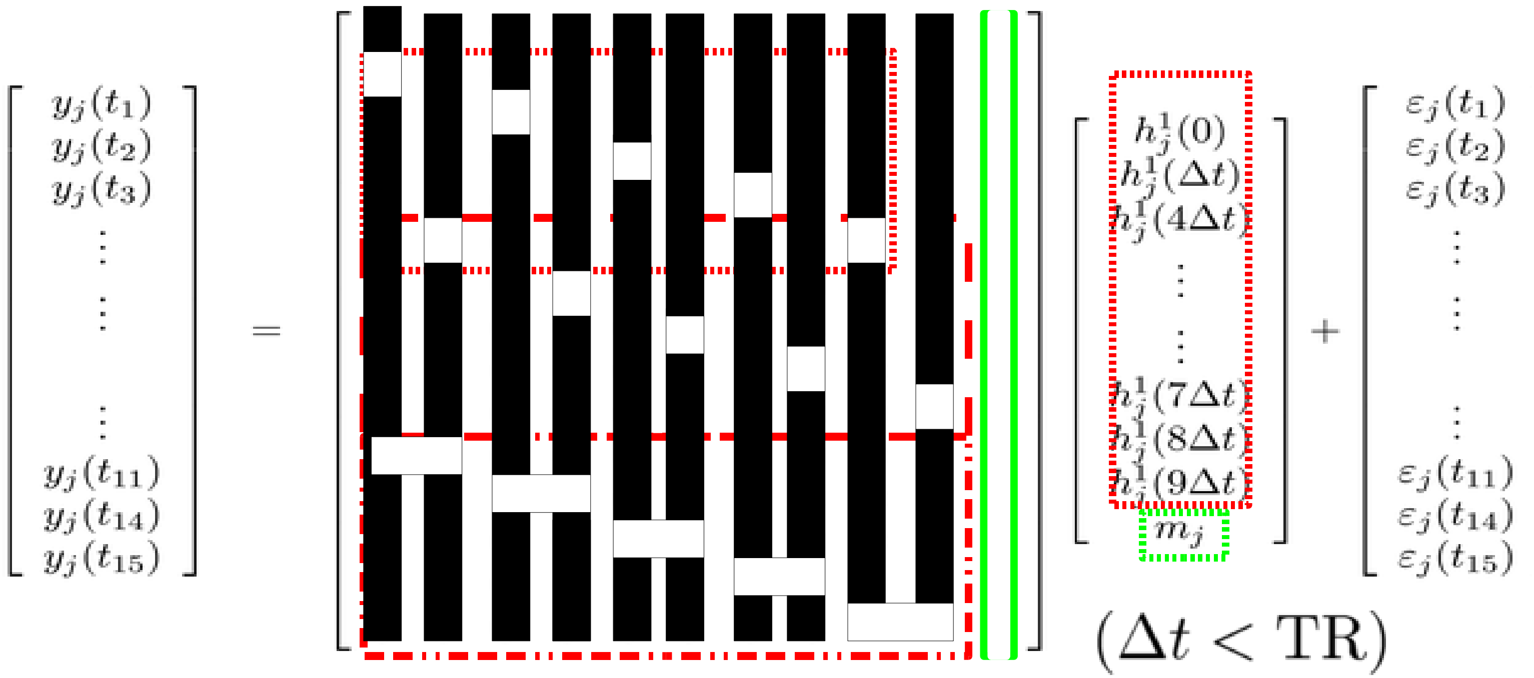
$$\boldsymbol{y}_j = [\boldsymbol{X}^1 \,|\, \boldsymbol{X}^2 \,|\, \boldsymbol{1}] \begin{bmatrix} \boldsymbol{h}_j^1 \\ \boldsymbol{h}_j^2 \\ m_j \end{bmatrix} + \boldsymbol{\varepsilon}_j$$

$$= \sum_{m=1}^{M} \boldsymbol{X}^m \boldsymbol{h}^m + m_j \boldsymbol{1} + \boldsymbol{\varepsilon}_j$$



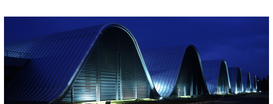
over-sampled FIR model

- Design matrix for estimating a single HRF
  - 3 events



$$\boldsymbol{y}_j = \left[\boldsymbol{X}^1 \,|\, \boldsymbol{X}^2 \,|\, \boldsymbol{1}\right] \begin{bmatrix} \boldsymbol{h}_j^1 \\ \boldsymbol{h}_j^2 \\ m_j \end{bmatrix} + \boldsymbol{\varepsilon}_j$$

$$= \sum_{m=1}^{M} \boldsymbol{X}^m \boldsymbol{h}^m + m_j \boldsymbol{1} + \boldsymbol{\varepsilon}_j$$



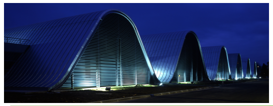
Actual fMRI experiments

- Possible extension to multisession datasets
  - HRF fixed across sessions
  - Session-varying low frequency fluctuations
  - Session-dependent noise statistics

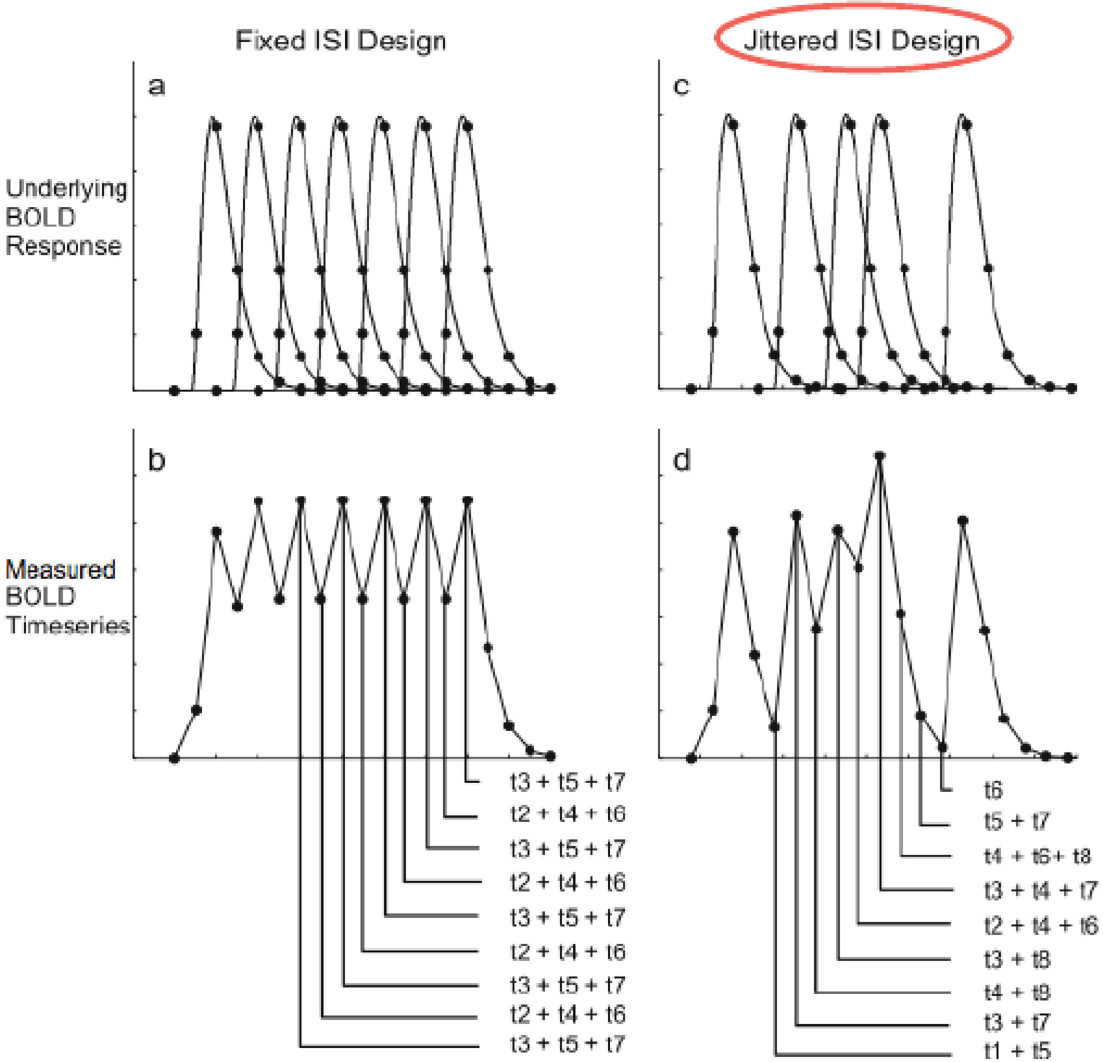
Fixed effect model:

$$\forall s, \quad \boldsymbol{y}_j^{(s)} = \sum_{m=1}^{M} \boldsymbol{X}_s^m \boldsymbol{h}^m + \boldsymbol{P}_s \boldsymbol{\ell}_j^{(s)} + \boldsymbol{\varepsilon}_j^{(s)}$$

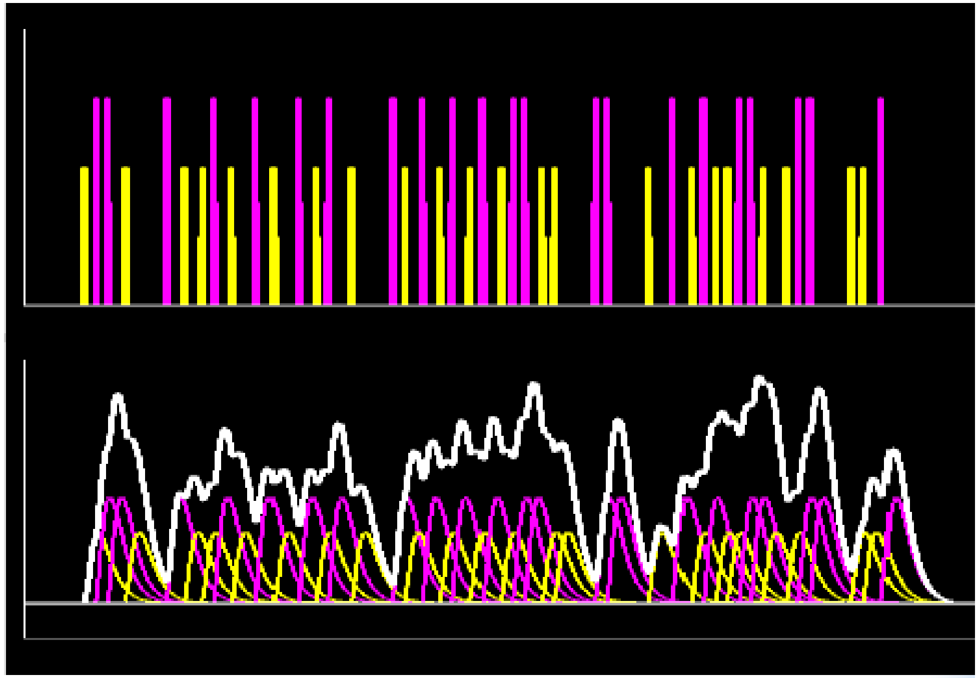
- Noise assumptions
  - homoscedasticity: $\sigma^2_{\varepsilon^{(s)}} = \sigma^2, \forall s$
  - heteroscedasticity: $\sigma^2_{\varepsilon^{(s)}} \neq \sigma^2_{\varepsilon^{(t)}}$ for $s \neq t$
- Alternative: Random effect model
  - Session dependent HRF
  - Test HRF mean over sessions



FIR estimation efficiency

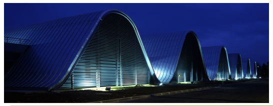


Best estimation efficiency:
jittered ISI and
randomised event order



Bayesian inference

$$\underbrace{p(\mathrm{HRF}\,|\,\mathrm{data})}_{\text{Posterior distribution}} = \frac{\overbrace{p(\mathrm{data}\,|\,\mathrm{HRF})}^{\text{likelihood}}\;\overbrace{p(\mathrm{HRF})}^{\text{Prior distribution}}}{\underbrace{p(\mathrm{data})}_{\text{evidence}}}$$



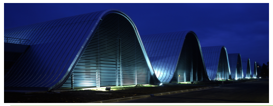
Bayes' rule

likelihood

$$p(\mathrm{HRF} \mid \mathrm{data}) = \frac{p(\mathrm{data} \mid \mathrm{HRF})\, p(\mathrm{HRF})}{p(\mathrm{data})}$$

How the data are generated from the HRF?

Forward modeling



Forward BOLD signal model

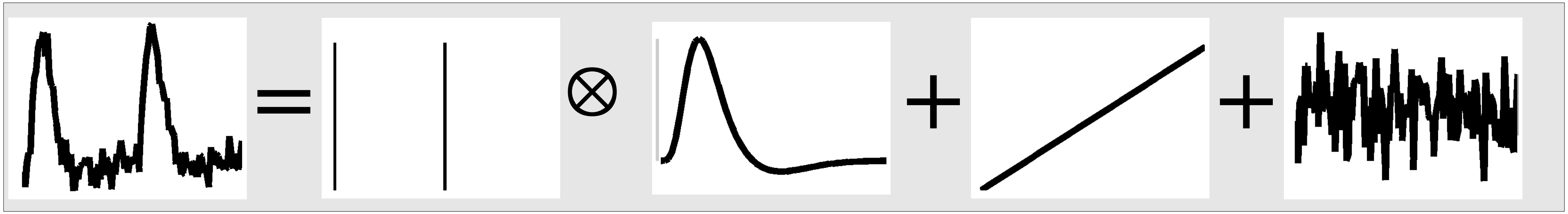
Unknown parameters

HRF

Drift

Noise statistics voxel V_j

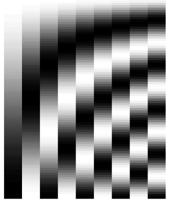
$$\boldsymbol{y}_j = \sum_{m=1}^{M} \boldsymbol{X}^m \boldsymbol{h}_j^m + \boldsymbol{P}\boldsymbol{\ell}_j + \boldsymbol{b}_j$$

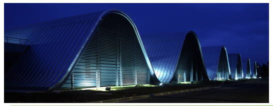


BOLD signal measured in voxel V_j

Arrival time of stimulus m

Orthonormal basis for low frequency drift modelling





Known parameters

Likelihood definition

- **Main hypothesis: noise decorrelated in space**

➡ fMRI time series are statistically independent in space:

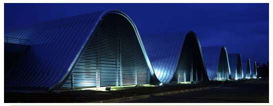
$$p(\mathbb{y} \mid \mathbb{h}, \mathbb{l}, \boldsymbol{\theta}_0) = \prod_{j=1}^{J} p(\boldsymbol{y}_j \mid \boldsymbol{h}_j, \boldsymbol{\ell}_j, \theta_{0,j})$$

$$\propto \prod_{j} f_{B_j}\left(\boldsymbol{y}_j - \sum_{m=1}^{M} \boldsymbol{X}^m \boldsymbol{h}_j^m - \boldsymbol{P}\boldsymbol{\ell}_j\right)$$

Temporal noise model: either white or serially correlated AR(1)

$\boldsymbol{b}_j \sim \mathcal{N}(\mathbf{0}, \epsilon_j^2 \boldsymbol{I})$ ➡ $\theta_{0,j} = [\epsilon_j^2]$

$\boldsymbol{b}_j \sim \mathcal{N}(\mathbf{0}, \epsilon_j^2 \boldsymbol{\Lambda}_j^{-1})$ ➡ $\theta_{0,j} = [\epsilon_j^2, \rho_j]$



[Marrelec et al, HBM 2003; Ciuciu et al, IEEE TMI 2003]

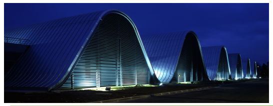
Bayes' rule

Prior

$$p(\mathrm{HRF} \mid \mathrm{data}) = \frac{p(\mathrm{data} \mid \mathrm{HRF})\, p(\mathrm{HRF})}{p(\mathrm{data})}$$

What do we know about the HRF before the data are acquired?

Prior modeling

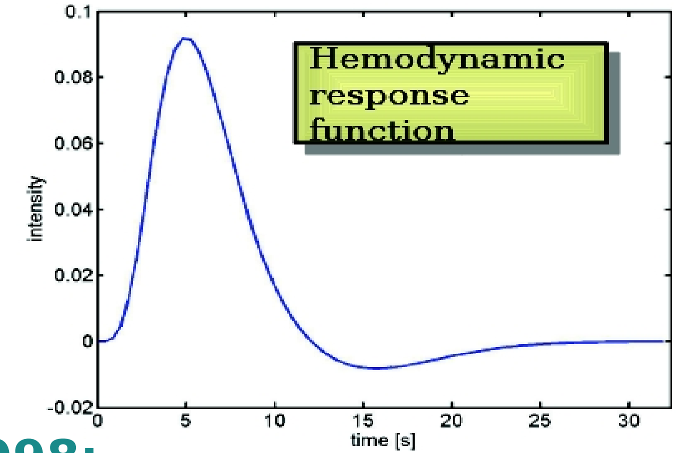


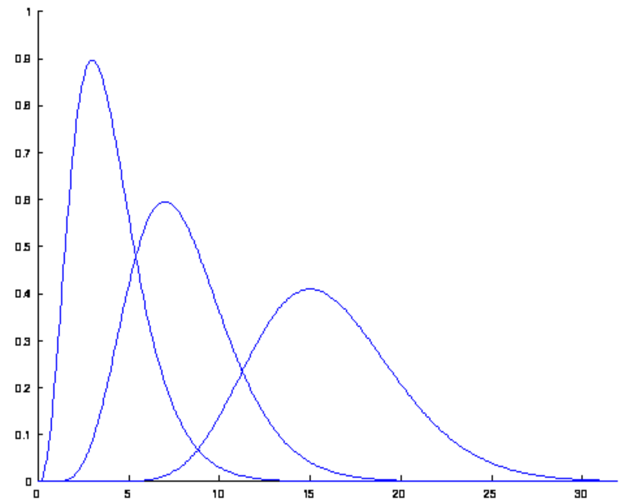
HRF prior modelling

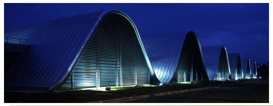
Parametric approaches

- Canonical HRF: SPM **[Friston et al, 1994]**
- One function, several parameters
  - Poisson functions: **[Friston et al, 1994]**
  - Gamma functions: **[Boyton et al, 1996]**
  - Gaussian functions: **[Rajapakse et al, 1998; Kruggel & von Cramon, 1999; Kruggel et al, 2000]**

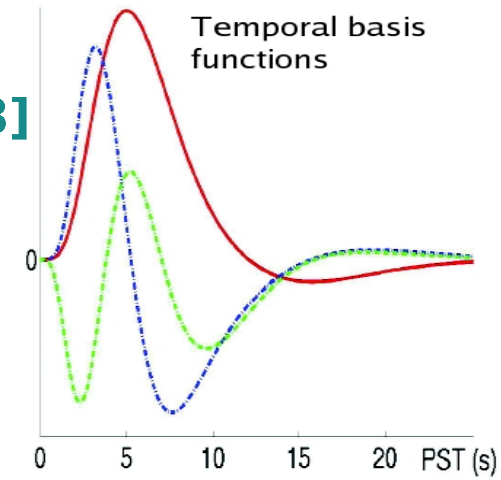
canonical HRF







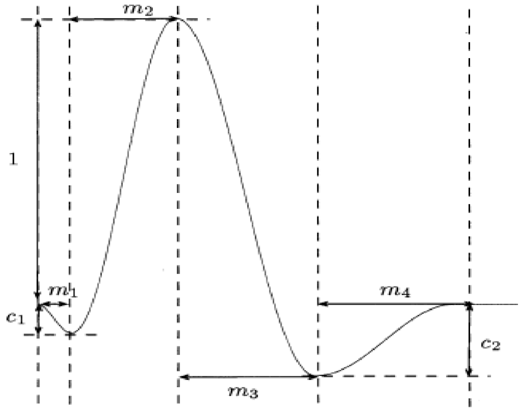
HRF prior modelling

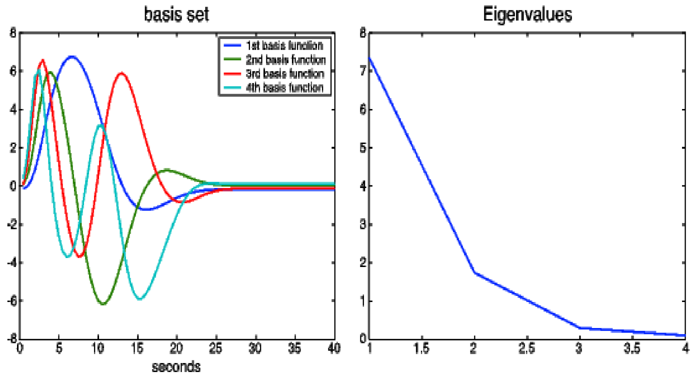


- **Function basis** [Friston et al, NIM 1998]
  - Gamma function and its derivative(s)
  - polynomial/spline functions:

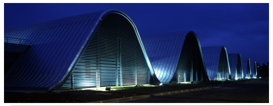
[Genovese, JASA 2000; Gössl et al, NIM 2001; Gibbons et al, 2004]

  - Half-cosine parameterization:





[Woolrich et al, NeuroImage 2004]



HRF prior modelling

[Marrelec, Ciuciu et al, IPMI'03; Ciuciu et al., 2003]

- **Nonparametric approach: smoothing prior**

•$\boldsymbol{h}_m$ is $C^2 \Longrightarrow \boldsymbol{h}_m \sim \mathcal{N}(0, r_m \boldsymbol{R})$ with $r_m > 0$, and $\boldsymbol{R}^{-1} = \boldsymbol{D}_2^{\mathrm{t}} \boldsymbol{D}_2$

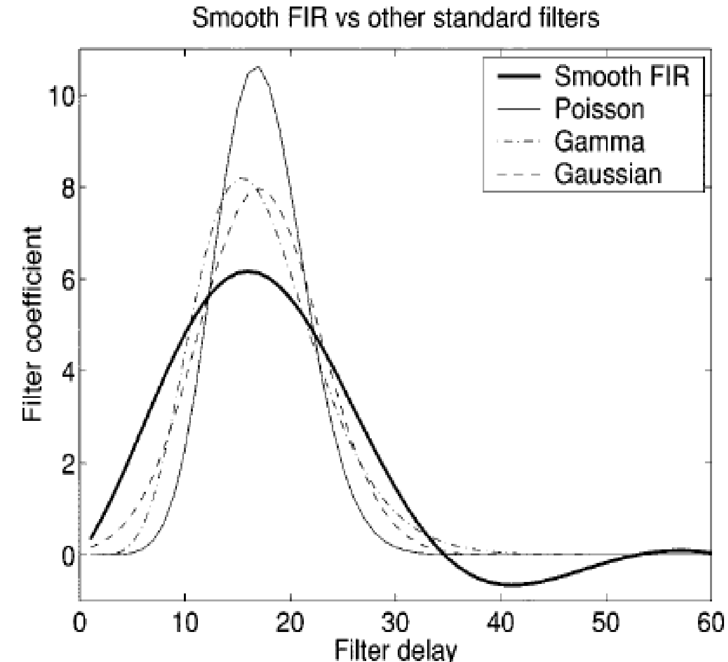
•$\boldsymbol{h}_m \approx 0$ at the stimulus onset and the baseline return: $h_{0,m} = h_{P\Delta t,m} = 0$

•$\boldsymbol{h}_m$ and $\boldsymbol{h}_k$ are independent for $m \neq k$:

$$p(\boldsymbol{h}\,;\,\boldsymbol{R}, \boldsymbol{\theta_h}) = \prod_{m=1}^{M} p(\boldsymbol{h}_m \,|\, \boldsymbol{R}, r_m)$$

$$\propto \left(\prod_{m=1}^{M} r_m^{-(P-1)/2} \right) \det(\boldsymbol{R})^{-M/2} \exp\left(-\frac{\boldsymbol{h}^{\mathrm{t}} \boldsymbol{R}_{\boldsymbol{h}}^{-1} \boldsymbol{h}}{2} \right)$$

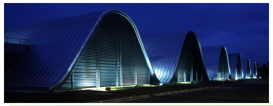
with $\boldsymbol{R_h} = \mathrm{diag}\,[\boldsymbol{r}] \otimes \boldsymbol{R} = \mathrm{diag}\,[r_1 \boldsymbol{R}, r_2 \boldsymbol{R}, \ldots, r_M \boldsymbol{R}]$, $\boldsymbol{\theta_h} = [r_1, \ldots, r_M]$



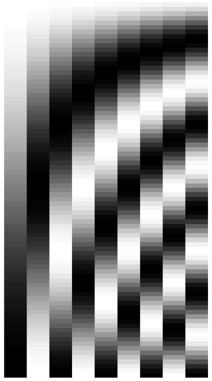
$$\boldsymbol{D}_{2,} = \frac{1}{(\Delta t)^2} \begin{pmatrix} -2 & 1 & 0 & & & & \\ 1 & -2 & 1 & 0 & & & \\ 0 & 1 & -2 & 1 & 0 & & \\ & \ddots & \ddots & \ddots & \ddots & \ddots & \\ & & 0 & 1 & -2 & 1 & 0 \\ & & & 0 & 1 & -2 & 1 \\ & & & & 0 & 1 & -2 \end{pmatrix}$$

$$(\partial^2 \boldsymbol{h})_{i,k\Delta t} \approx \frac{h_{i,(k+1)\Delta t} - 2h_{i,k\Delta t} + h_{i,(k-1\Delta t)}}{(\Delta t)^2}$$

$$\|\partial^2 \boldsymbol{h}_i\|^2 = (\boldsymbol{D}_{2,i} \boldsymbol{h}_i)^t (\boldsymbol{D}_{2,i} \boldsymbol{h}_i) = \boldsymbol{h}_i^t \left(\boldsymbol{D}_{2,i}^t \boldsymbol{D}_{2,i} \right) \boldsymbol{h}_i.$$

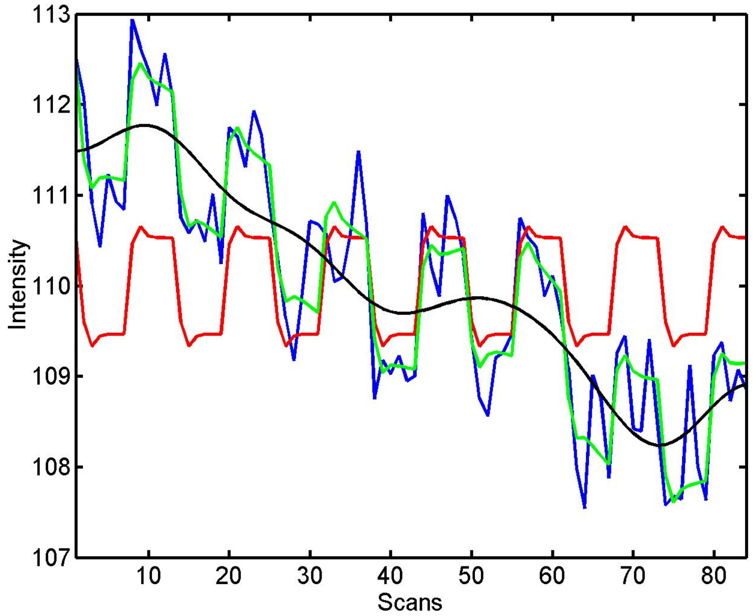


Drift modelling

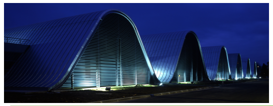


Parametric approaches

- Linear subspace spanned by
  - DCT basis function: **[Friston et al, 2000]**
  - A set of polynomial basis function: [**Worsley et al, 2000]**
- Wavelet subspace: **[Meyer, 2003]**



Reduce autocorrelation in the residual noise process

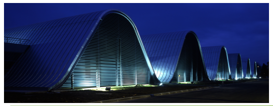


Bayes' rule

$$p(\mathrm{HRF} \,|\, \mathrm{data}) \propto p(\mathrm{data} \,|\, \mathrm{HRF}) \, p(\mathrm{HRF})$$

What do we know about the HRF given the data?

Keystone of learning scheme



Bayesian HRF estimate

- Closed-form MAP estimate

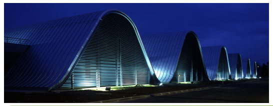
$$p(\boldsymbol{h}_j \,|\, \boldsymbol{y}_j \;;\, \boldsymbol{\theta}, \boldsymbol{\ell}_j) \sim \mathcal{N}(\widehat{\boldsymbol{h}}_j^{\,\mathrm{MAP}}, \boldsymbol{\Sigma}_j)$$

$$\boldsymbol{\Sigma}_j^{-1} = \frac{1}{\sigma_{\varepsilon_j}^2} \boldsymbol{X}^{\mathrm{t}} \boldsymbol{X} + \boldsymbol{R}_{\boldsymbol{H}}^{-1},$$

$$\widehat{\boldsymbol{h}}_j^{\,\mathrm{MAP}} = \frac{1}{\sigma_{\varepsilon_j}^2} \boldsymbol{\Sigma} \boldsymbol{X}^{\mathrm{t}} \left(\boldsymbol{y}_j - \boldsymbol{P}\boldsymbol{\ell}_j\right)$$

- Alternative Marginal MAP estimate:

$$\widehat{\boldsymbol{h}}_j^{\,\mathrm{MMAP}} = \arg\max_{\boldsymbol{h}} p(\boldsymbol{h} \,|\, \boldsymbol{y}_j \;;\, \boldsymbol{\theta}) = \arg\max_{\boldsymbol{h}} \int p(\boldsymbol{h}, \boldsymbol{\ell}_j \,|\, \boldsymbol{y}_j \;;\, \boldsymbol{\theta})\, d\boldsymbol{\ell}_j.$$



Drift & hyper-parameters

- Nuisance variables and hyper-parameters
  - Deterministic parameters: Maximum likelihood estimation

$$(\widehat{\boldsymbol{\theta}}^{\mathrm{ML}}, \widehat{\boldsymbol{\ell}}_j{}^{\mathrm{ML}}) = \arg\max_{\boldsymbol{\theta}, \boldsymbol{\ell}_j} \big[\log p(\boldsymbol{y}_j \; ; \boldsymbol{\theta}, \boldsymbol{\ell}_j) = \log \int p(\boldsymbol{y}_j, \boldsymbol{h}_j \; ; \boldsymbol{\theta}, \boldsymbol{\ell}_j)\, d\boldsymbol{h}_j\big]$$

  - EM or ECM algorithm **[Ciuciu et al, IEEE TMI 2003]**
  - Drift parameters as random variables: marginalization

$$\widehat{\boldsymbol{\theta}}^{\mathrm{ML}} = \arg\max_{\boldsymbol{\theta}} \big[\log p(\boldsymbol{y}_j \; ; \boldsymbol{\theta}) = \log \int p(\boldsymbol{y}_j, \boldsymbol{h}_j, \boldsymbol{\ell}_j \; ; \boldsymbol{\theta})\, d\boldsymbol{h}_j \, d\boldsymbol{\ell}_j\big]$$

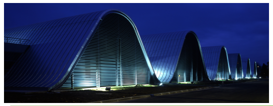
[Marrelec, Ciuciu, IEEE TMI 2004]

  - Hyper-parameters as random variables: combine marginalization & posterior inference using sampling

$$p(\boldsymbol{\theta}_0, \boldsymbol{h}_j \,|\, \boldsymbol{y}_j) = \int p(\boldsymbol{\theta}_0, \boldsymbol{\theta}_1, \boldsymbol{h}_j, \boldsymbol{\ell}_j \,|\, \boldsymbol{y}_j)\, d\boldsymbol{\theta}_1 \, d\boldsymbol{\ell}_j$$

$$\begin{cases} \boldsymbol{\theta}_0^{(k)} & \sim \quad p(\boldsymbol{\theta}_0 \,|\, \boldsymbol{h}_j^{(k-1)}, \boldsymbol{y}_j) \\ \boldsymbol{h}_j^{(k)} & \sim \quad p(\boldsymbol{h}_j \,|\, \boldsymbol{\theta}_0^{(k)}, \boldsymbol{y}_j) \end{cases}$$

[Marrelec et al, HBM 2003]



FIR vs. regularized FIR

[Casanova et al, NeuroImage, 2008]

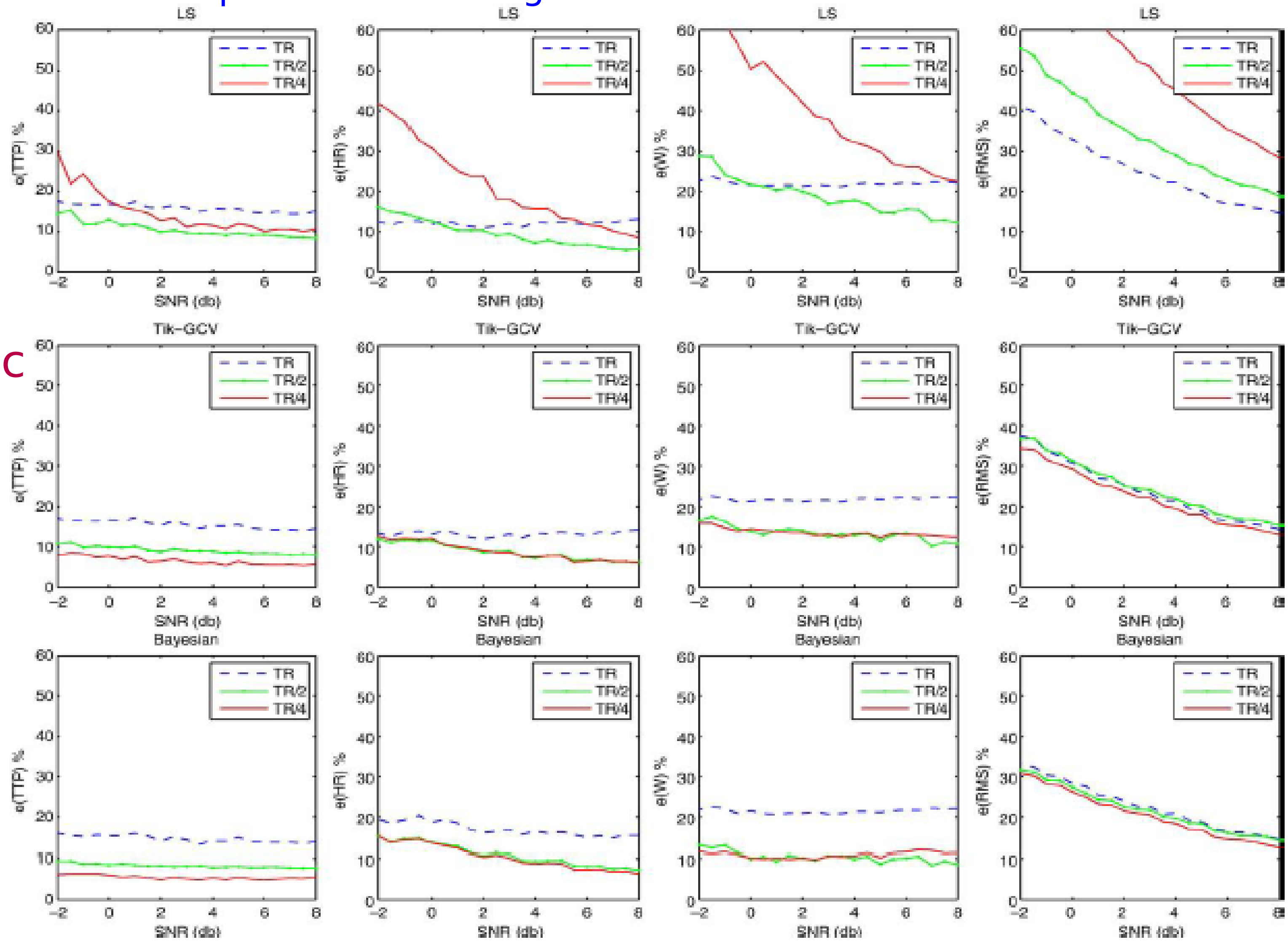
Increased temporal resolution with regularization

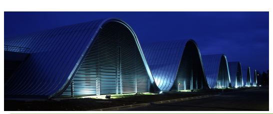
Time-to-peak | Height | Width | Root Mean Square Error

FIR

Deterministic regularized FIR

“Bayesian regularized FIR”





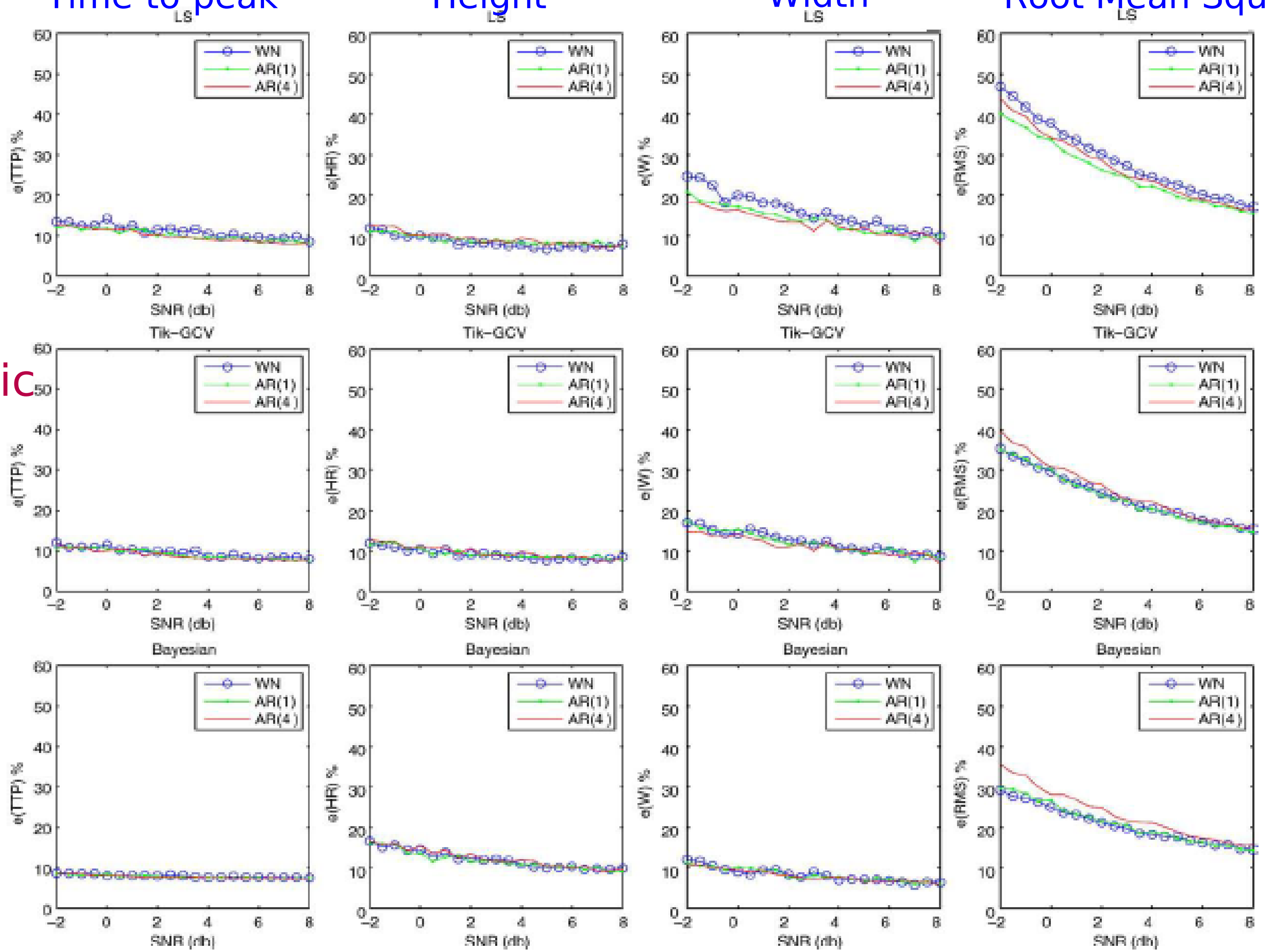
FIR vs. regularized FIR

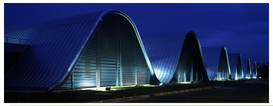
Time-to-peak | Height | Width | Root Mean Square Error

Exp. ITI pdf
ITI_{mean}=3s
FIR

Deterministic regularized FIR

"Bayesian regularized FIR"





Little impact of noise autocorrelation for short ISIs

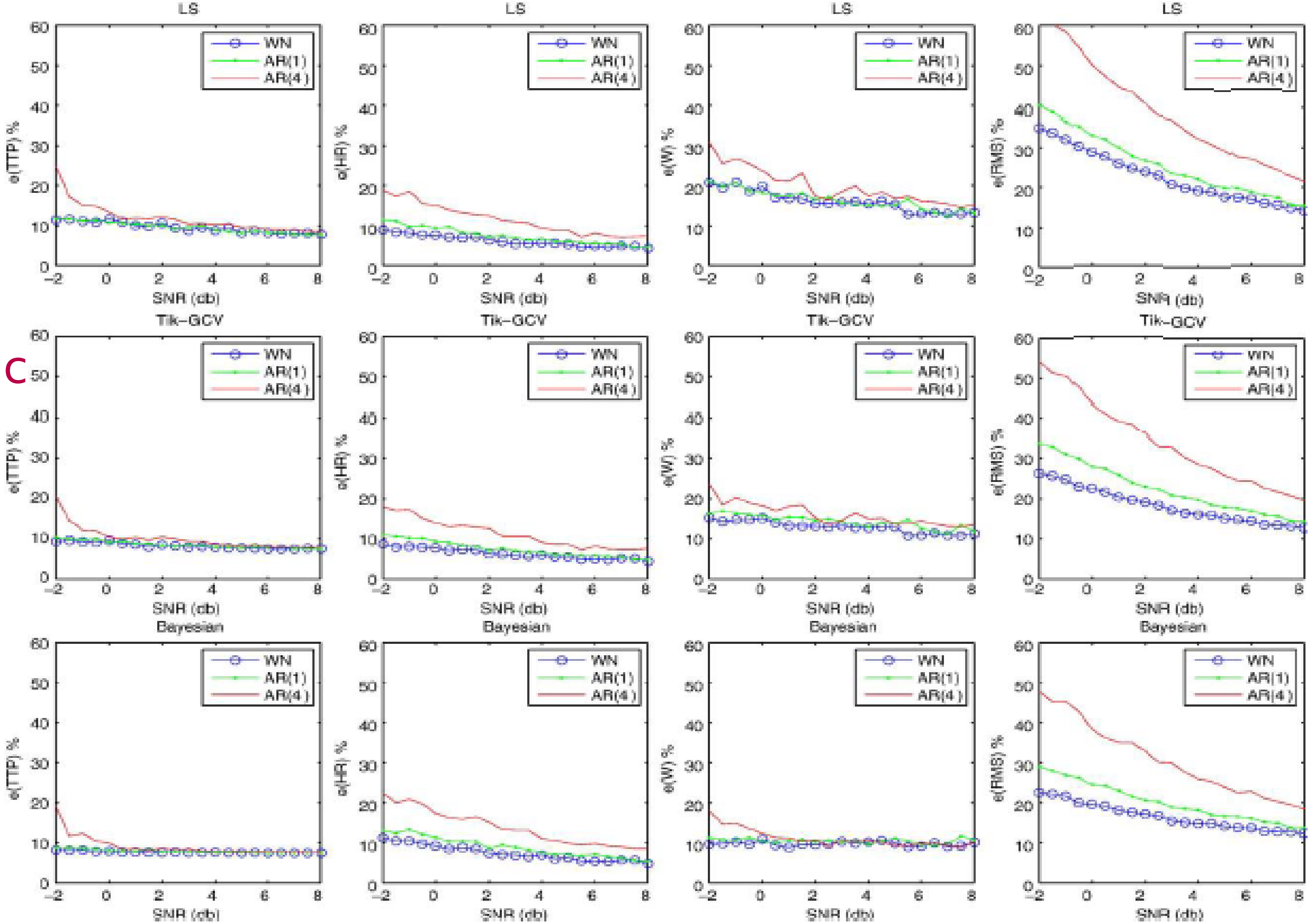
FIR vs. regularized FIR

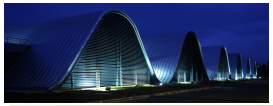
Time-to-peak | Height | Width | Root Mean Square Error

Exp. ISI pdf
ITI_{mean} =10s
FIR

Deterministic regularized FIR

“Bayesian regularized FIR”





Stronger impact of noise autocorrelation for long ITIs irrespective of the method

FIR vs. regularized FIR

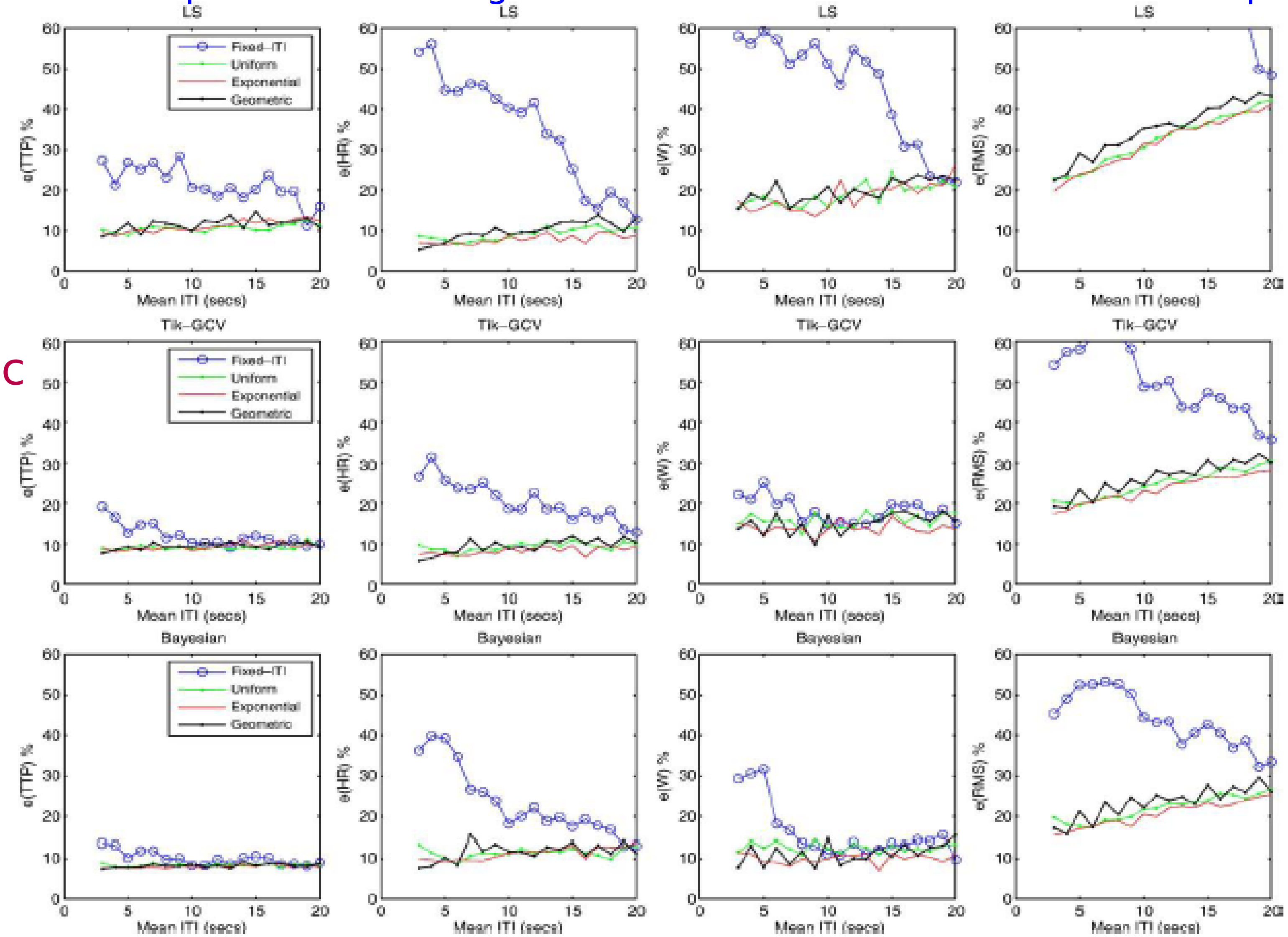
Time-to-peak | Height | Width | Root Mean Square Error

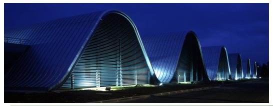
Various ITI densities

FIR

Deterministic regularized FIR

“Bayesian regularized FIR”

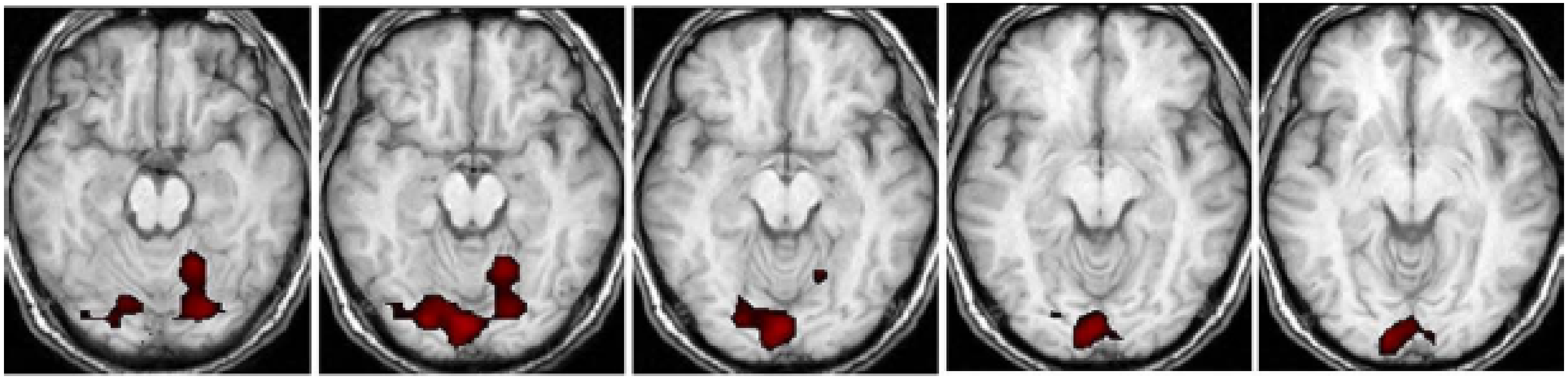


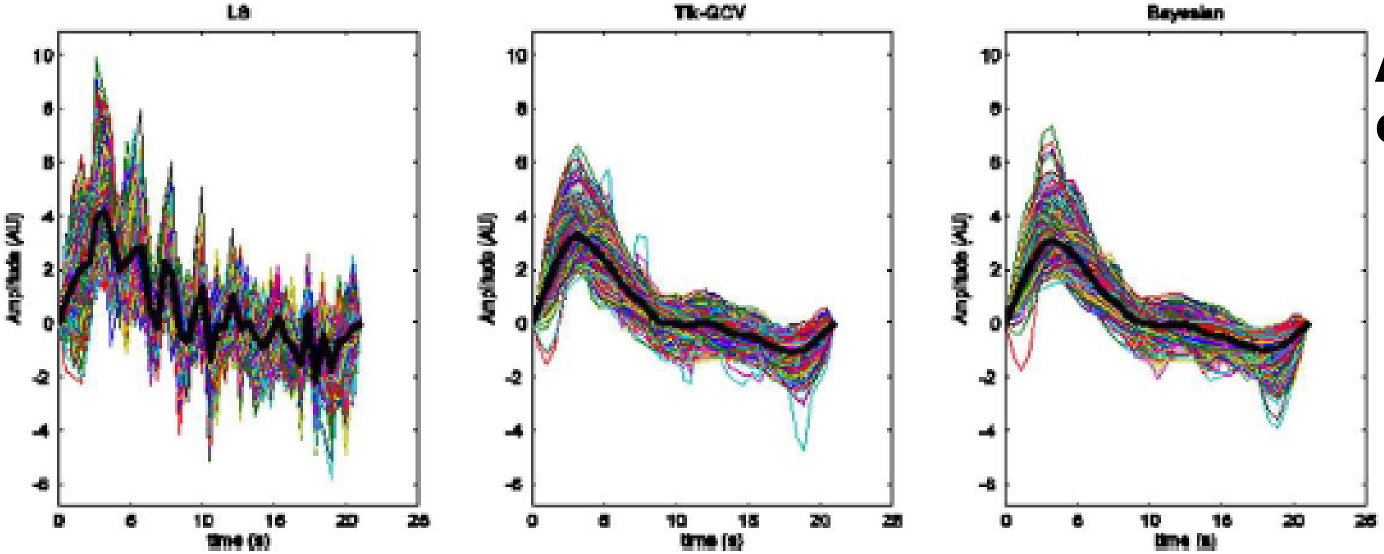


Regularization increases estimation efficiency at fixed ITI and performs even better using random designs

FIR/regularized FIR: real data

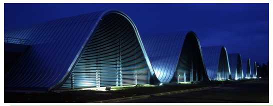
[Casanova et al, NeuroImage, 2008]



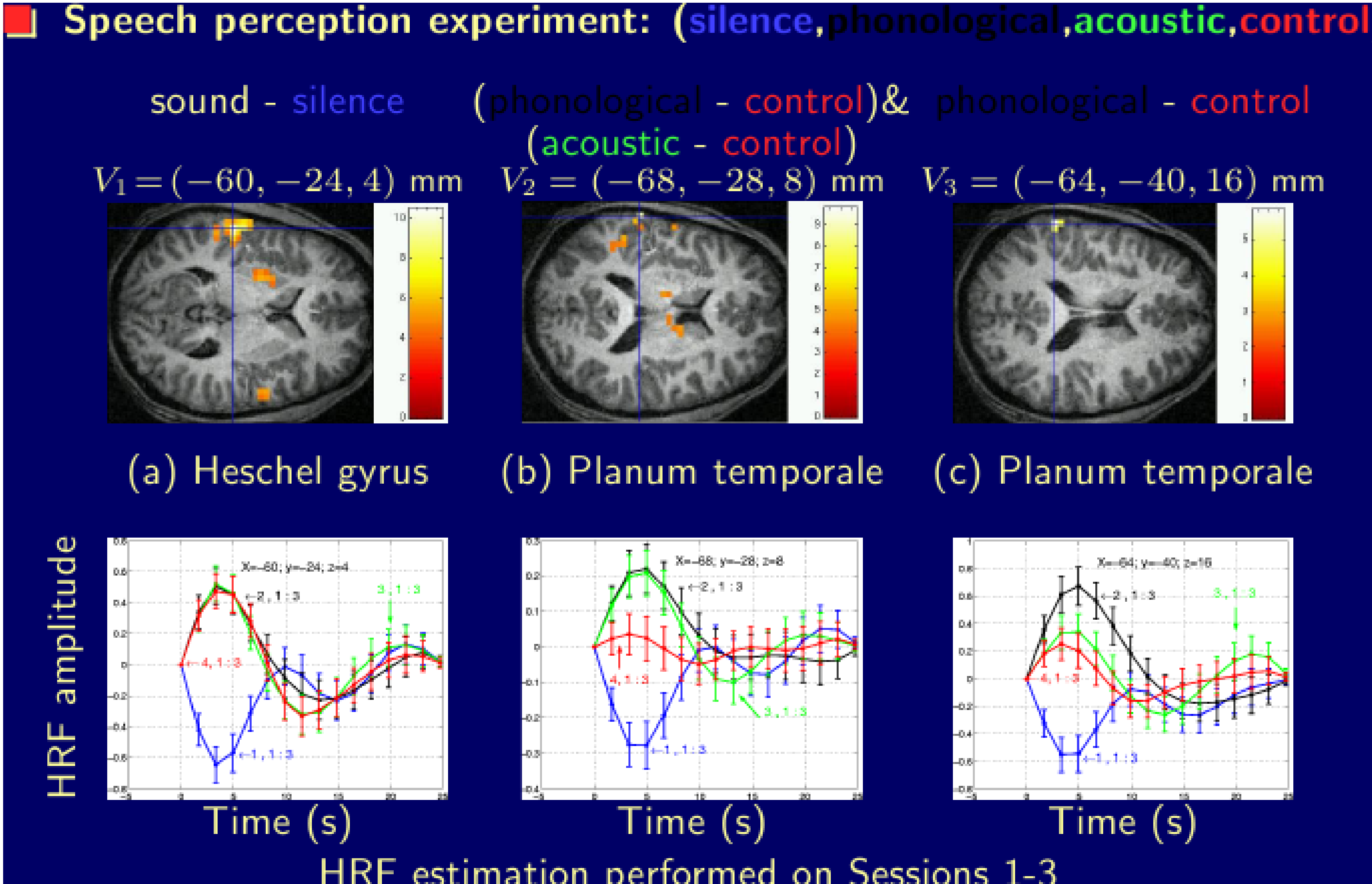


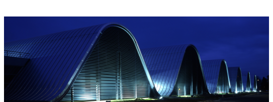
Average HRF estimate

Standard FIR estimates: unstable for TR/4 temporal grid
Regularized FIR models: similar & meaningful results



Results on real fMRI datasets





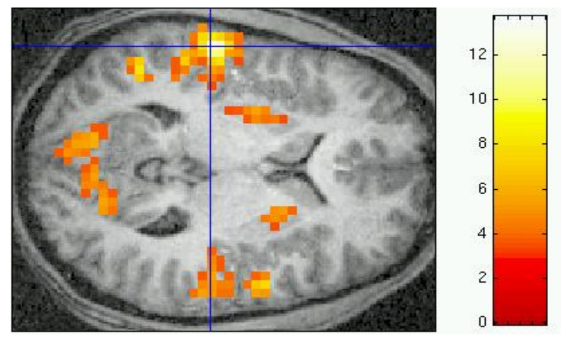
[Ciuciu et al, IEEE TMI, 2003]

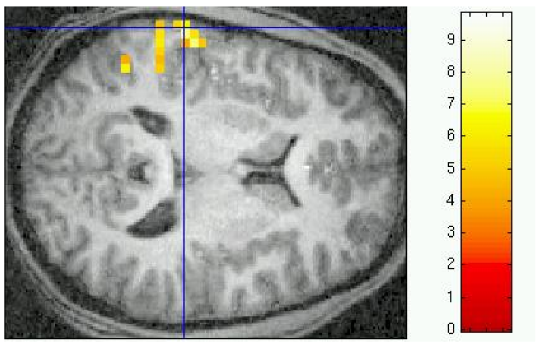
Improved detection

Better sensitivity [Ciuciu et al, ISBI, 2002]

GLM built using HRF estimate

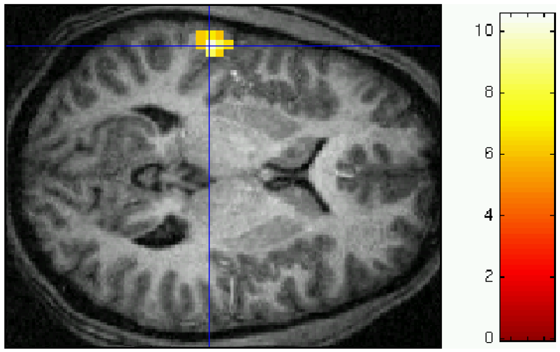
$$f_m(t_n) \stackrel{\Delta}{=} (x^{(m)} \star \hat{h}_m)(t_n)$$

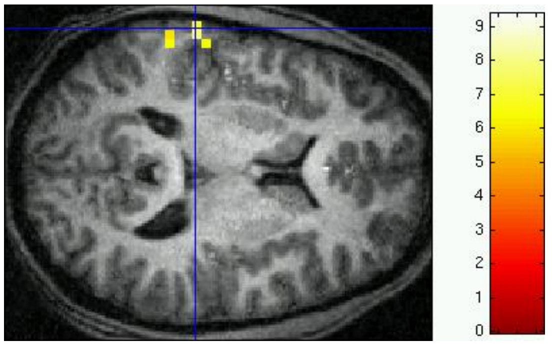




GLM built upon canonical HRF

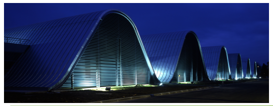
$$f_m(t_n) \stackrel{\Delta}{=} (x^{(m)} \star h_c)(t_n)$$





$V_1 = (-60, -24, 4)$ mm

$V_2 = (-68, -28, 8)$ mm



Between-trial variability

- Modelling the trial by trial variability

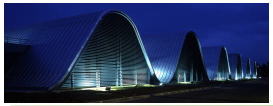
$$\boldsymbol{y}_j = \sum_{m=1}^{M}\sum_{k=1}^{K_m} \alpha_k^m \boldsymbol{X}_k^m \boldsymbol{h}_j + \boldsymbol{P}\boldsymbol{\ell}_j + \boldsymbol{b}_j$$

- Independence between trial magnitudes $\boldsymbol{\alpha} = (\alpha_k^m)$

[Donnet, Ciuciu et al, ISBI 2004]

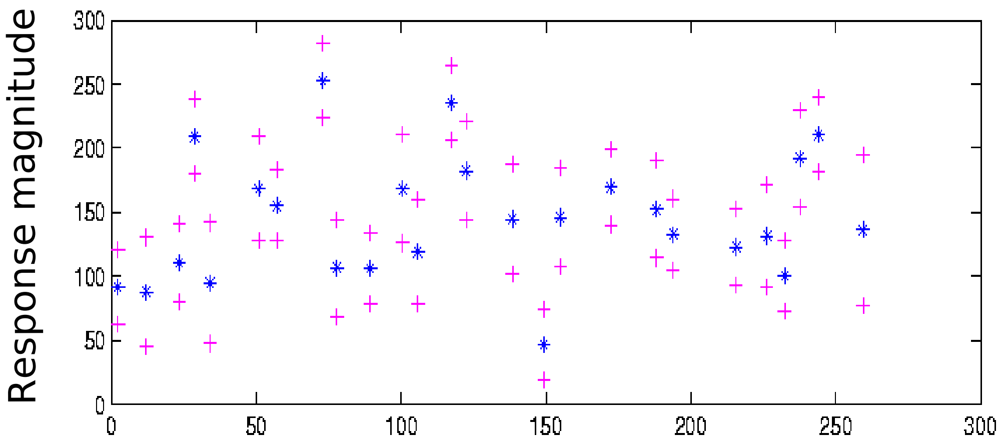
- Dependence on the past:
  - Habituation modelling: repetition-suppression phenomenon

[Ciuciu et al, ICASSP 2009]

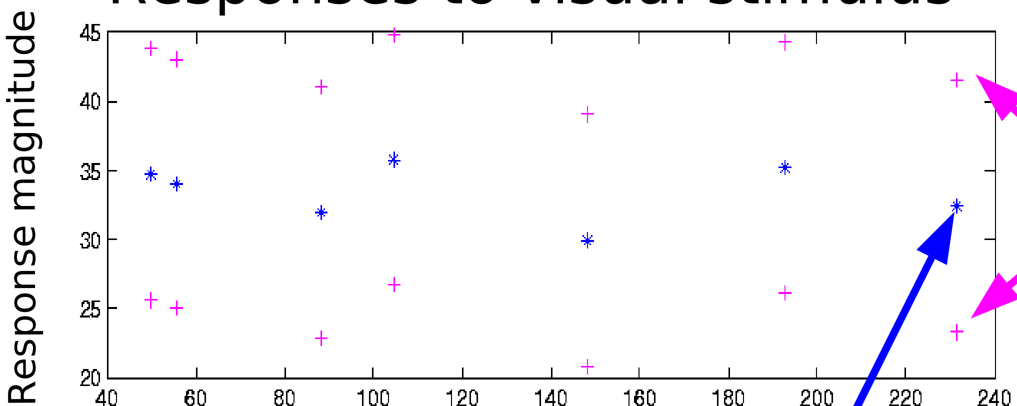


Extract temporal information

Responses to right button click

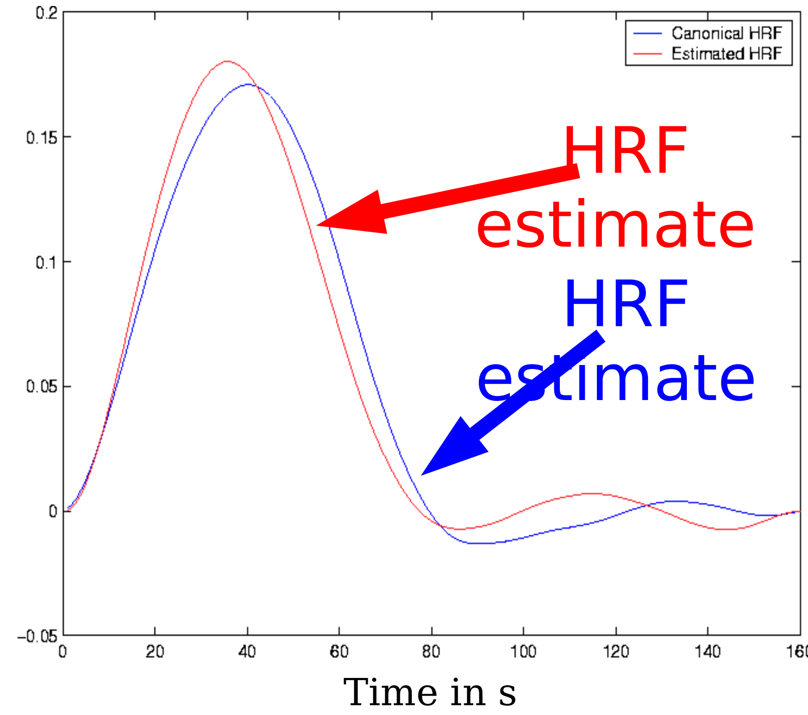


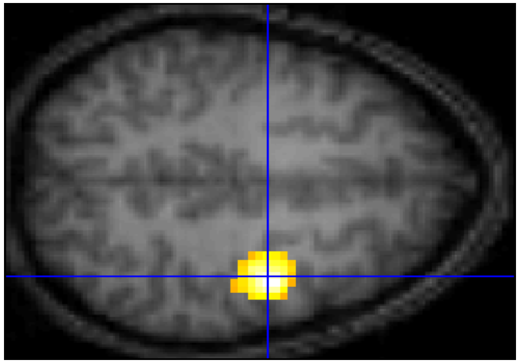
Responses to visual stimulus



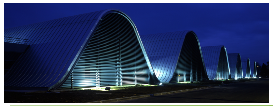
Standard deviation

Trial magnitude





Data from left motor cortex

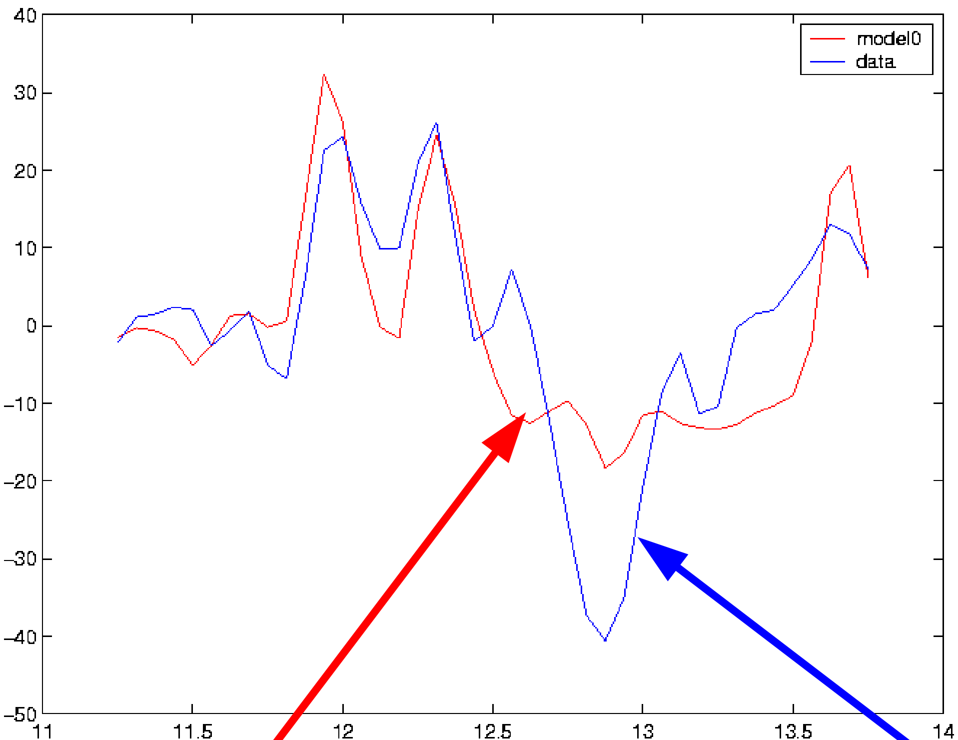


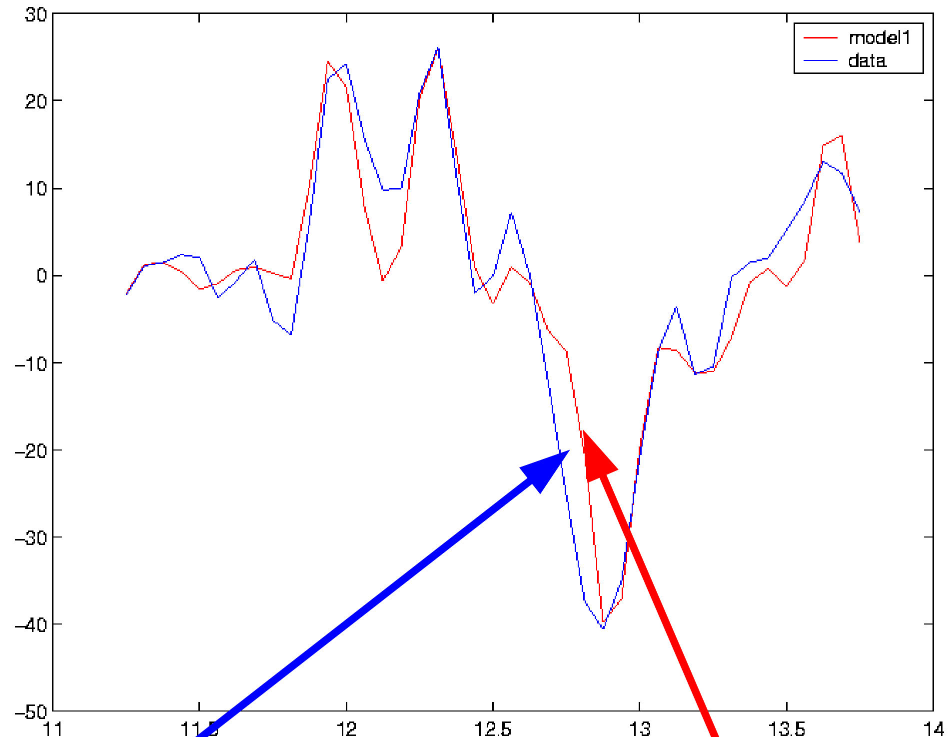
[Donnet et al., NeuroImage 2006]

Extract temporal information

$\mathcal{P} = \{\text{visual}, \text{Right click}\}$

[Donnet et al., ISBI 2004]

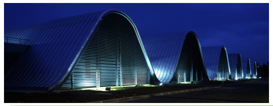




Predicted time series with a convolution model

Predicted time series by a non-stationary model

same fMRI time course



Conclusions

- Precise estimation of the evoked BOLD response
  - Efficient & random design
  - Reasonable Signal-to-Noise ratio
  - Regularization necessary

- FIR modelling
  - Sufficient for ITI > 2s.
  - Otherwise: inadequate to capturing non-linear effects
  - Able to account for trial-by-trial variability

- Voxelwise HRF estimation approaches
  - Computationally costly
  - Only a scanner induced spatial resolution
  - ... Less robust than regionwise counterparts