Joint Estimation of Activity Signal and HRF in fMRI using Fused LASSO

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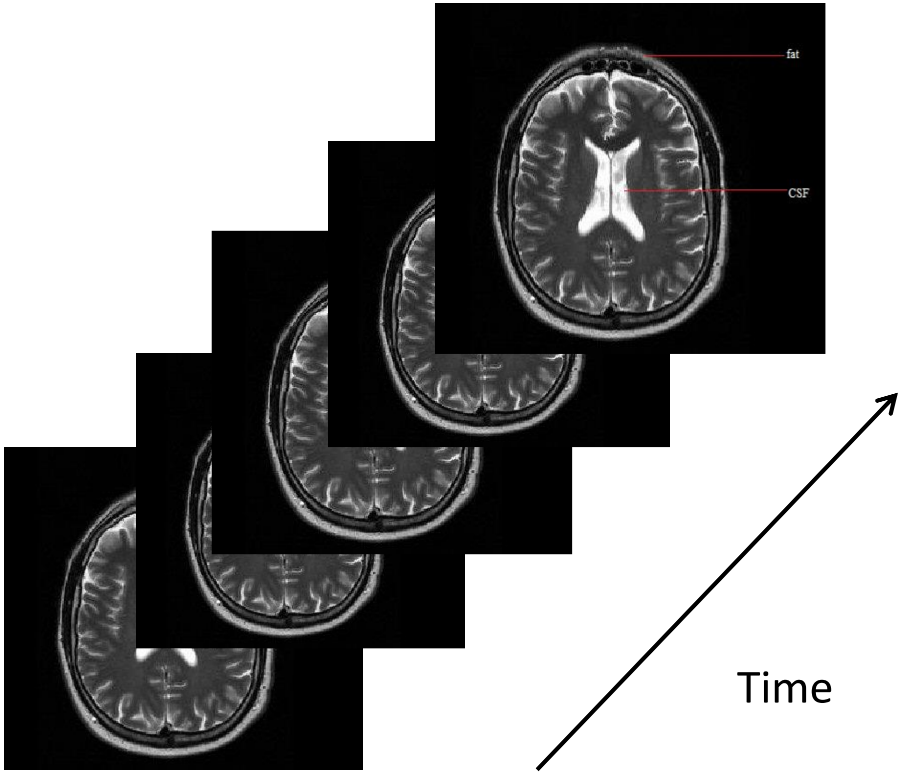
Presented by: Anubha Gupta

Outline of the Presentation

- Motivation
- Proposed work on joint estimation of HRF and activity signal
- Validation of the proposed method
    - on synthetic data
    - on real fMRI data
- Conclusion

Functional Brain Imaging (fMRI)



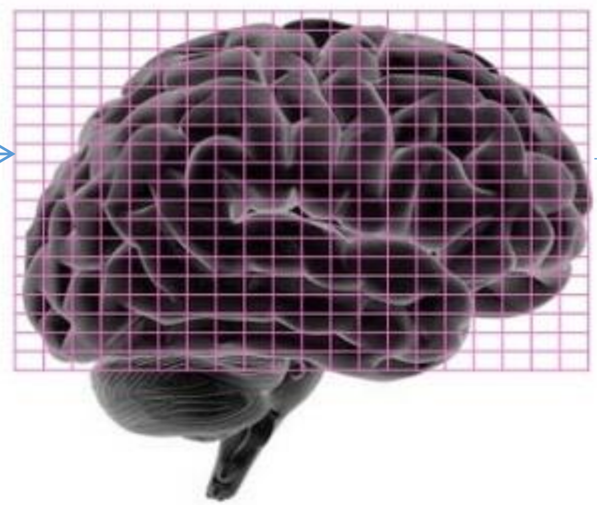
fMRI signal processing

Input stimulus to perform cognitive task

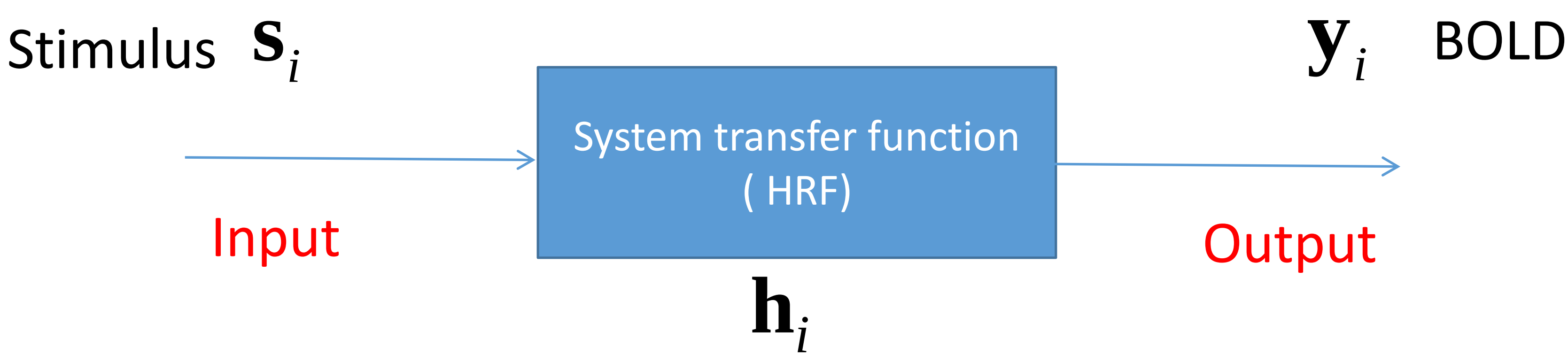
Detect brain activity

Output

Input



Motivation



fMRI voxel time series

$$\mathbf{y}_i = \mathbf{s}_i \otimes \mathbf{h}_i + \xi_i \qquad \text{......(1)}$$

Prior work for estimating activity signal

fixed canonical HRF

$$\mathbf{y}_i = \mathbf{s}_i \otimes \mathbf{h}_i + \boldsymbol{\xi}_i \qquad \text{......(1)}$$

$$\mathbf{y}_i = \mathbf{S}\mathbf{h}\alpha_i + \boldsymbol{\xi}_i \qquad \text{-----(2)}$$

- Only unknown in equ.1 is intrinsic stimuli

HRF shape may vary across different brain regions as well as across patients.

Proposed Work

Aim: To propose a method for the joint estimation of HRF and activity signal

Proposed Joint Estimation Framework

1. Estimate underlying activity signal => via fused LASSO

2. Refine the HRF estimate

Iteratively

Step-1: Estimation of activity signal

$$\mathbf{y}_i = \mathbf{s}_i \otimes \mathbf{h}_i + \boldsymbol{\xi}_i$$

$$\mathbf{y}_i = \mathbf{H}_i \mathbf{s}_i + \boldsymbol{\xi}_i \qquad \text{......(3)}$$

BOLD signal Convolution matrix AR(1)

Unknown activity signal

Contd..

Fused LASSO

$$\hat{\mathbf{s}}_i = \underset{\mathbf{s}_i}{\arg\min} \|\mathbf{R}_v(\mathbf{y}_i - \mathbf{H}_i\mathbf{s}_i)\|_2 + \lambda_0\|\mathbf{s}_i\|_1 + \lambda_1\|\mathbf{T}\mathbf{s}_i\|_1$$

noise whitening matrix

......(4)

noise covariance matrix $\mathbf{\Gamma}$ ($\mathbf{\Gamma}^{-1} = \mathbf{R}_v^T\mathbf{R}_v$)

$$\mathbf{\Gamma} = \frac{\sigma_v^2}{1-\rho^2}\begin{bmatrix} 1 & \rho & \rho^2 & \ldots & \rho^{n-1} \\ \rho & 1 & \rho & \ldots & \rho^{n-2} \\ . & . & . & . & . \\ . & . & . & . & . \\ \rho^{n-1} & \ldots & \rho^2 & \rho & 1 \end{bmatrix}$$

$$\mathbf{T} = \begin{bmatrix} -1 & 1 & 0 & . & . & 0 & 0 \\ 0 & -1 & 1 & 0 & . & . & 0 \\ 0 & 0 & -1 & 1 & 0 & . & . \\ 0 & 0 & . & . & . & . & . \\ . & . & . & . & . & . & 0 \\ 0 & . & . & . & 0 & -1 & 1 \\ 0 & 0 & . & 0 & 0 & 0 & -1 \end{bmatrix}$$

Step-2: Estimation of HRF

$$\mathbf{y}_i = \mathbf{s}_i \otimes \mathbf{h}_i + \boldsymbol{\xi}_i$$

$$\mathbf{y}_i = \mathbf{S}_i \mathbf{h}_i + \boldsymbol{\xi}_i \qquad \text{......(5)}$$

BOLD signal Convolution matrix AR(1)

Unknown HRF

Step-2: Estimation of HRF

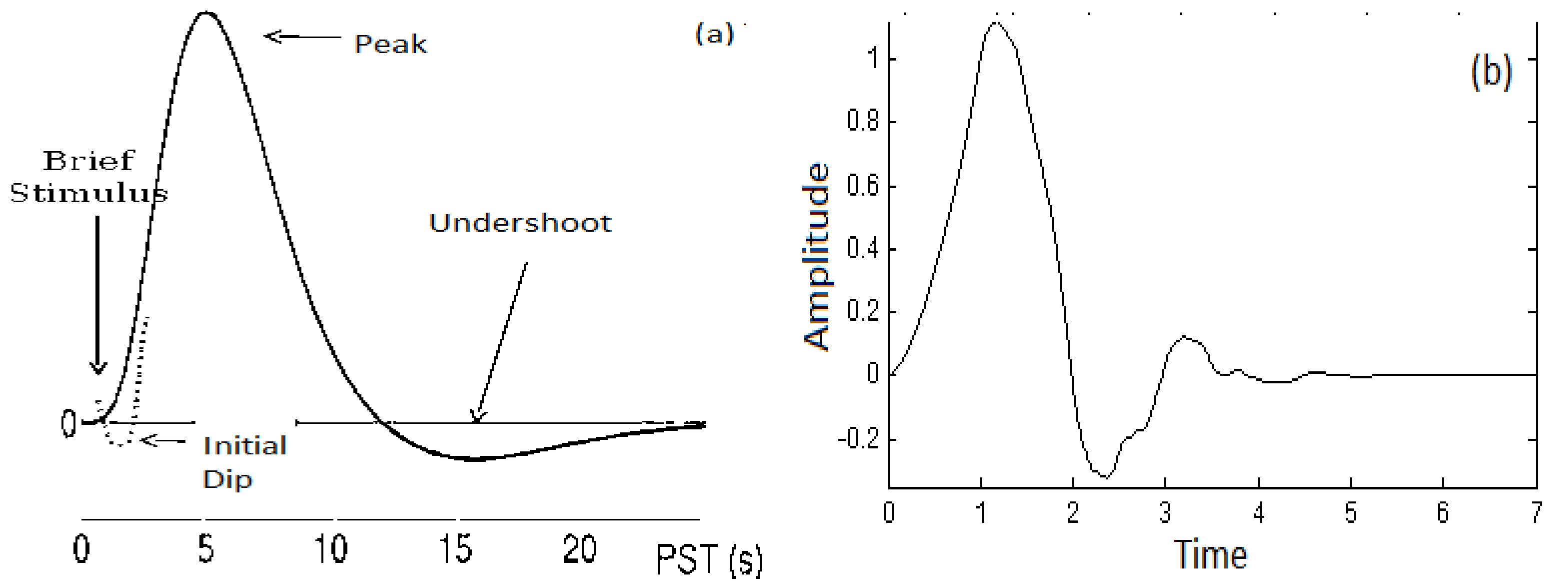


Fig. 1. (a):Theoretical shape of HRF; (b) Scaling function of *db4*

Assumptions on HRF:

1) Smooth over time; 2) Sparse in wavelet domain (with db4)

Contd.

$$\hat{\mathbf{h}}_i = \underset{h_i}{argmin} \left\| \mathbf{R}_v (\mathbf{y}_i - \mathbf{S}_i \mathbf{h}_i) \right\|_2 + \lambda_2 \left\| \mathbf{D} \mathbf{h}_i \right\|_2 + \lambda_3 \left\| \mathbf{W} \mathbf{h}_i \right\|_1$$

……(6)

$$\mathbf{D} = \begin{bmatrix} 2 & -1 & 0 & . & . & 0 & 0 \\ -1 & 2 & -1 & 0 & . & . & 0 \\ 0 & -1 & 2 & -1 & 0 & . & . \\ 0 & 0 & . & . & . & . & . \\ . & . & . & . & 2 & -1 & 0 \\ 0 & . & . & . & -1 & 2 & -1 \\ 0 & 0 & . & 0 & 0 & -1 & 2 \end{bmatrix}$$

Matrix operator for *db4*

Table-1

Pseudo Code for the Iterative Joint Estimation framework

Input Parameters

Tikhonov regularisation matrix **D** (size L x L)

Fused LASSO matrix **T** (size M x M)

Daubechies-4 matrix **W** (size L x L)

Initialize HRF matrix $\mathbf{H}_i$ (size M x M)

Lagrangian multipliers λ_1, λ_2, and λ_3 (scalars)

Noise covariance matrix Γ

Input Data

Measured voxel V_i's time series stacked in a column $\mathbf{r}_i$ (size M x 1)

Start

Step-1 $\mathbf{y}_i$=detrend($\mathbf{r}_i$)

Step-2 Compute estimate of activity signal $\hat{\mathbf{s}}_i$

$$\hat{\mathbf{s}}_i = \arg\min_{\mathbf{s}_i} \|\mathbf{R}_v(\mathbf{y}_i - \mathbf{H}_i\mathbf{s}_i)\|_2 + \lambda_0\|\mathbf{s}_i\|_1 + \lambda_1\|\mathbf{T}\mathbf{s}_i\|_1$$

Step-3 Compute estimate of HRF $\hat{\mathbf{h}}_i$ using $\hat{\mathbf{s}}_i$

$$\hat{\mathbf{h}}_i = \arg\min_{\mathbf{h}_i} \|\mathbf{R}_v(\mathbf{y}_i - \mathbf{S}_i\mathbf{h}_i)\|_2 + \lambda_2\|\mathbf{D}\mathbf{h}_i\|_2 + \lambda_3\|\mathbf{W}\mathbf{h}_i\|_1$$

Repeat Step-2 and Step-3 until the shapes of $\hat{\mathbf{s}}_i$ and $\hat{\mathbf{h}}_i$ converge.

Output $\hat{\mathbf{h}}_i$ and $\hat{\mathbf{s}}_i$

Results on synthetic fMRI data

Synthetic HRF of length 32 is generated using the difference of two Gamma functions as below-

$$h[n] = \left(\frac{n}{a_1 b_1}\right)^{a_1} e^{\frac{-(n-a_1 b_1)}{b_1}} - c\left(\frac{n}{a_2 b_2}\right)^{a_2} e^{\frac{-(n-a_2 b_2)}{b_2}} \quad \text{......(7)}$$

with a_1=6, a_2=12, b_1=b_2=6, and c=0.35.

Synthetic stimulus of 200 time points is generated with 5 ON periods of duration 6s, 5s, 10sm 3s, and 1s with onsets at 10s, 40s, 100s, 140s, and 180s, respectively.

Results on synthetic fMRI data

- Black solid line shows the actual HRF used in simulation set-up
- Box plot shows estimated HRF over 500 realizations of noise time-series

$\lambda_0=0.001$, $\lambda_1=0.3$, $\lambda_2=1$, $\lambda_3=0.7$, $\sigma^2=0.1$

- Black solid line shows the actual stimulus used in simulation set-up
- Box plot shows estimated stimulus over 500 realizations of noise time-series

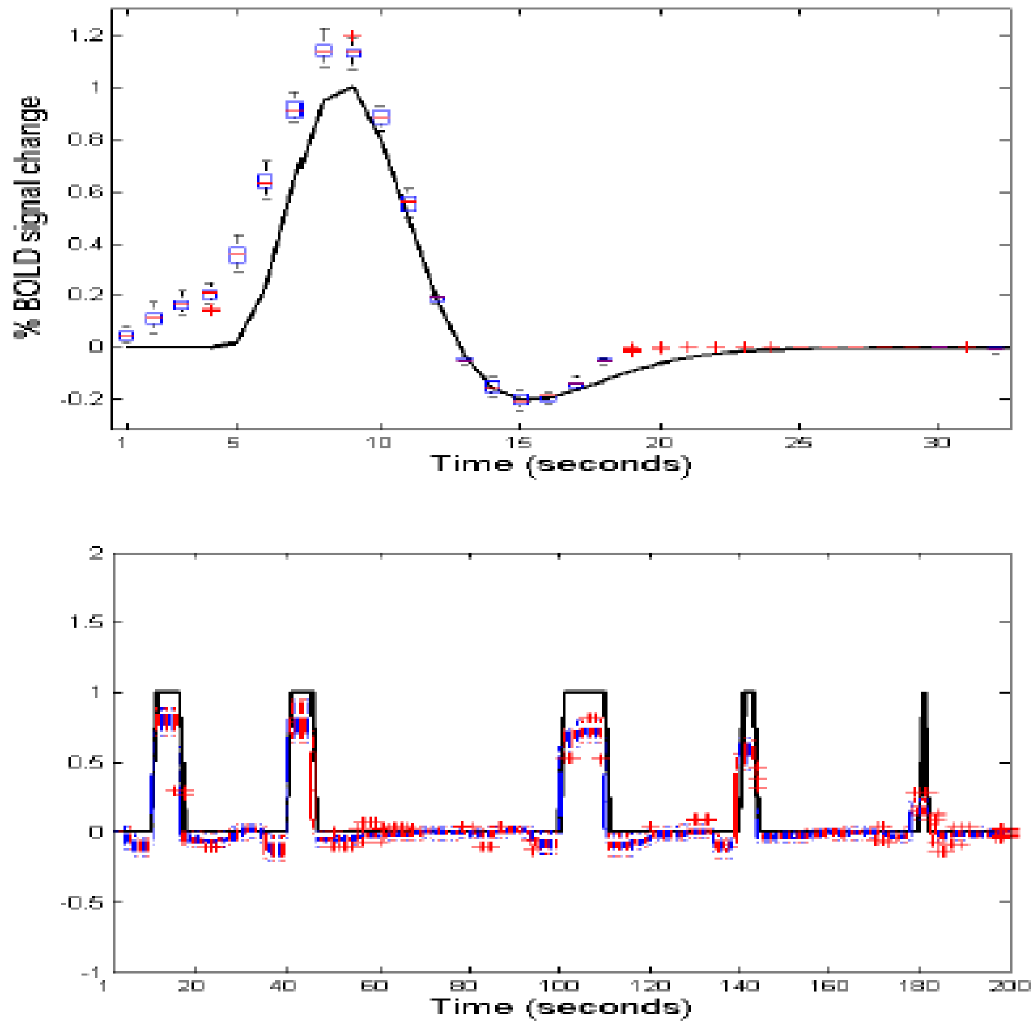


Fig. 2: (a): Estimated HRF; (b) Estimated Activity Signal

Contd.

Table-2: MSE calculated between estimated and the actual HRF (that is used in the synthetic data)

	Noise Variance σ^2				
	0.05	0.1	0.25	0.5	0.75
MSE using the Proposed method	0.0151	0.0159	0.0171	0.0183	0.0220

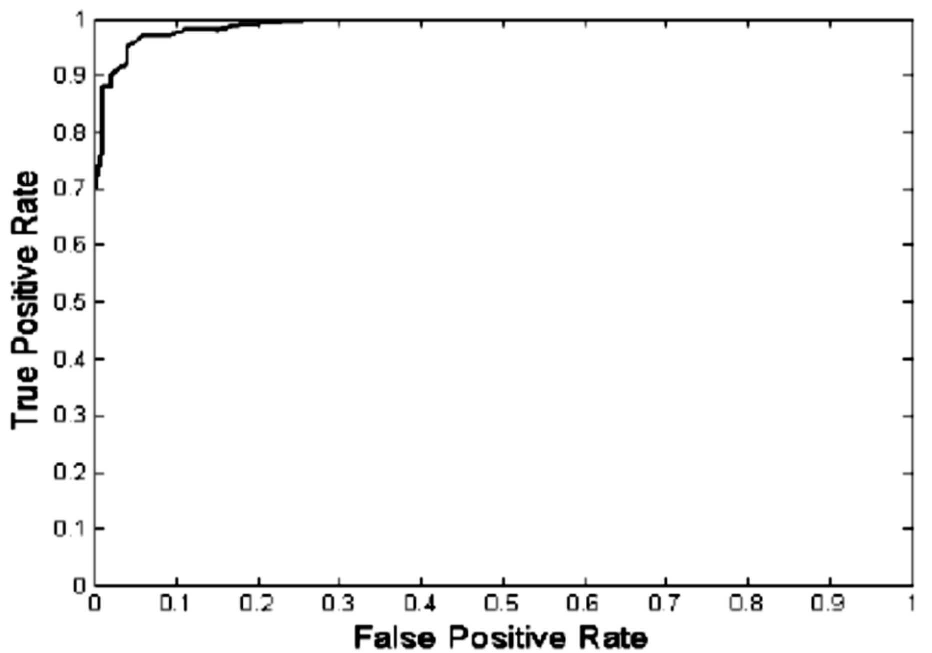


Fig.3: ROC curve on the estimated activity signal for single voxel time series with σ^2=0.25.

Results on real fMRI data

Real fMRI data --- a right hand finger tapping task in 3-T MR scanner

-- 36 contiguous slices with 128x128x36 voxels, voxel size = 4x4x4 mm^3

-- No. of brain volumes= 100, TR= 3s

-- Stimulus: 10 volumes of rest followed by 10 volumes of activity, and so on

-- Preprocessing: Using SPM12 -- include realignment (with the first scan for removal of motion artefact), slice time correction (with the first slice of each volume), and normalization (with the MNI atlas)

-- Resultant fMRI data had 100 brain volumes of 79x95x68 voxels each

-- No smoothing is done in preprocessing

-- First 12 dummy scans were discarded resulting in 88 brain volumes

Results on real fMRI data

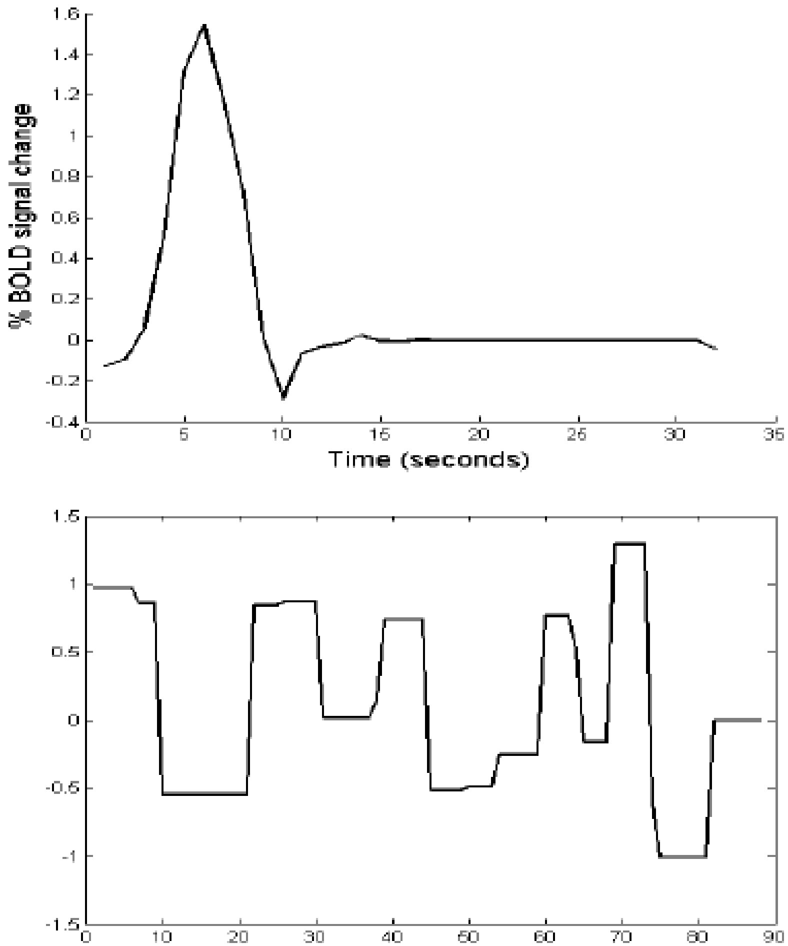


Fig. 5: (a): Estimated HRF; (b) Estimated Activity Signal at voxel (40, 43, 66) using the proposed method

Results on real fMRI data (Highest norm voxel)

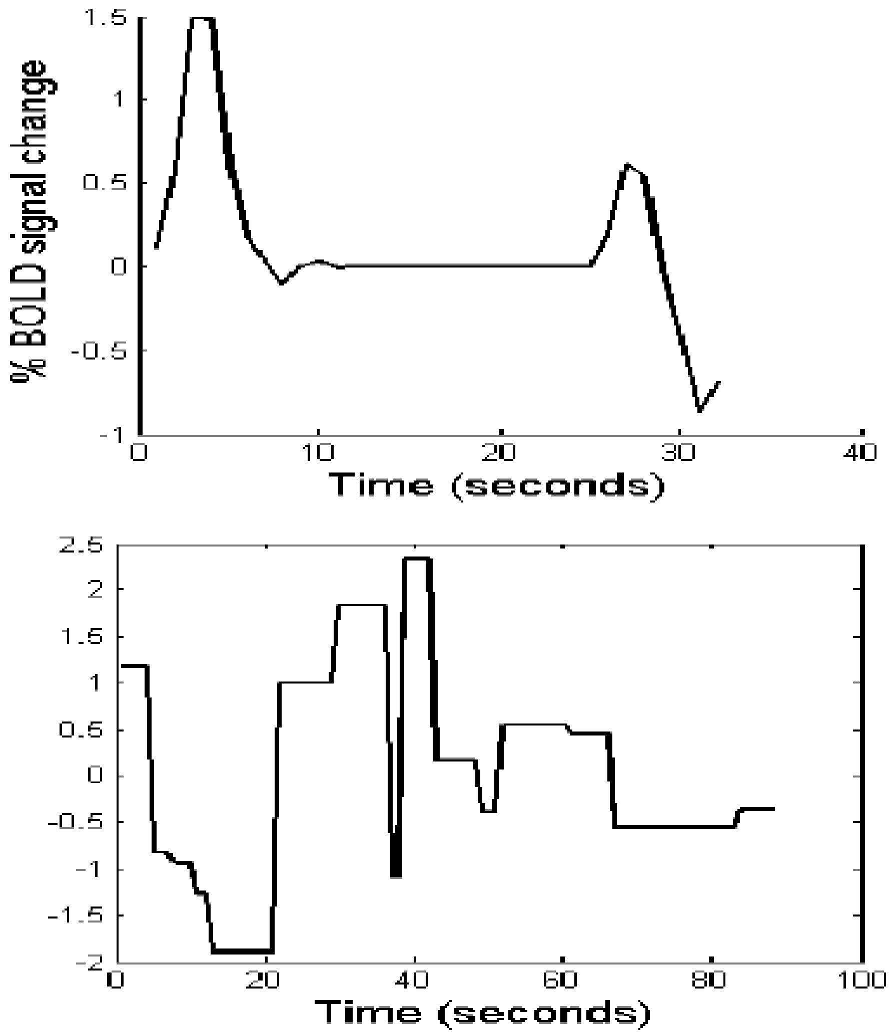


Fig. 6: (a): Estimated HRF; (b) Estimated Activity Signal at voxel (41, 45, 66) using the proposed method

Research contribution

- Joint iterative framework for the estimation of HRF and the underlying activity signal
- Two stage optimization that estimates activity signal and HRF iteratively
- Can be applied to both task-based and the Resting-state data
- The proposed method is observed to perform satisfactorily

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Thank you