Variational physiologically informed solution to hemodynamic and perfusion response estimation from ASL fMRI data

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Abstract

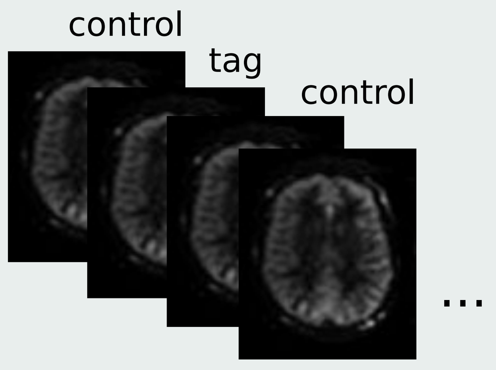
Functional Arterial Spin Labeling (fASL) [1] MRI can provide a quantitative measurement of cerebral blood flow and its variations elicited by specific tasks. The statistical analysis of fASL has been done using

- General linear model (GLM) [2] with regressors based on the canonical hemodynamic response function.
- Joint detection-estimation (JDE) [3] framework which allows the extraction of both task-related perfusion and hemodynamic responses not restricted to canonical shapes. Previous ASL-JDE attempts have been based on Markov Chain Monte Carlo (MCMC) methods, very computationally expensive.

Contribution: a variational expectation-maximization (VEM) algorithm [4] for hemodynamic and perfusion responses estimation.

Framework

ASL fMRI [1] data provide a quantitative measurement of blood perfusion changes elicited by task performance or stimulus delivery in the brain

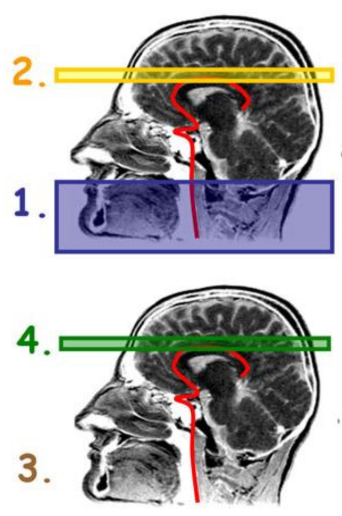


Magnetically tagged image (Tag)

Tag inflowing arterial blood by magnetic inversion

Control image

Repeat acquisition without labeling inflowing blood



Time delay (1) to (2): Labeled water reaches capillary bed and is exchanged with water molecules in the tissue

signal change

Control Image (4) - Tag Image (2)

$\uparrow - \uparrow = \uparrow \propto$ CBF

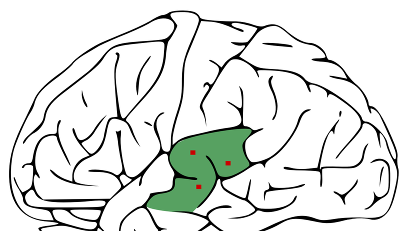
The difference in magnetization is proportional to regional cerebral blood flow

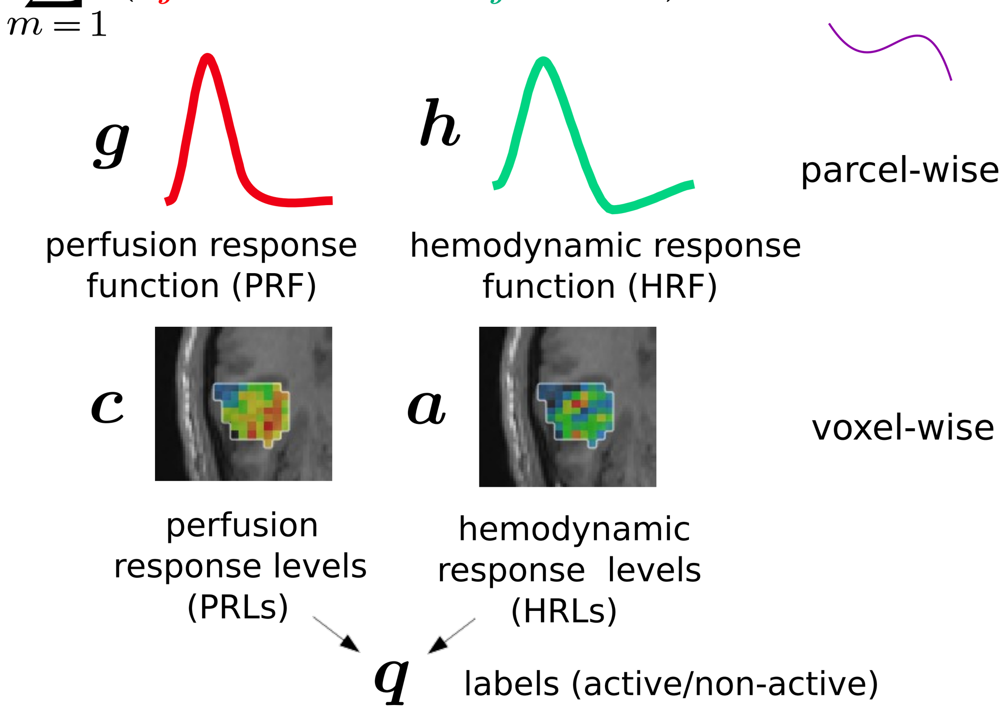
Ref: http://fmri.research.umich.edu/research/main_topics/asl.php

ASL Joint detection estimation (JDE) framework [3]

ASL signal	=	perfusion baseline	+	task-related perfusion	+	task-related BOLD	+	drift term	+	noise term

$$\boldsymbol{y}_j = \alpha_j \boldsymbol{w} + \sum_{m=1}^{M} \left(c_j^m \boldsymbol{W} \boldsymbol{X}^m \boldsymbol{g} + a_j^m \boldsymbol{X}^m \boldsymbol{h} \right) + \boldsymbol{P}\boldsymbol{\ell}_j + \boldsymbol{b}_j$$



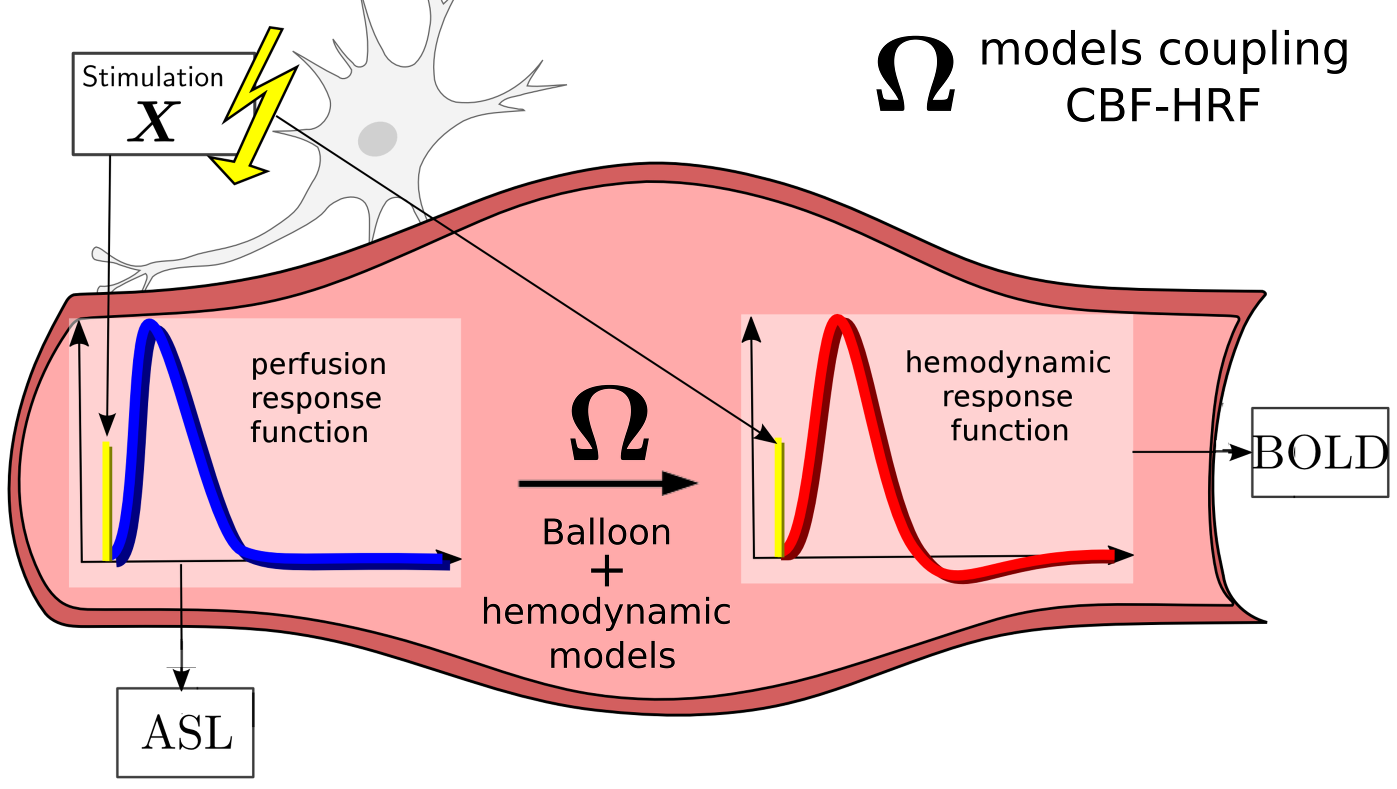


For every voxel in a parcel, ASL signal can be decomposed into different terms. We estimate the parameters of this model.

Physiologically informed JDE [5]

We consider physiological information in the estimation as a prior knowledge of the response functions $\mathbf{g} = \mathbf{\Omega}\mathbf{h}$

$\mathbf{\Omega}$ models coupling CBF-HRF



Variational Expectation-Maximization

Expectation-Maximization

E-step: $\tilde{p}^{(r)} = \arg\max_{\tilde{p}} F(\tilde{p}, \boldsymbol{\theta}^{(r)})$

M-step: $\boldsymbol{\theta}^{(r+1)} = \arg\max_{\boldsymbol{\theta}} F(\tilde{p}^{(r)}, \boldsymbol{\theta})$

Maximizing function F is equivalent to minimizing the Kullback-Leibler divergence between $\tilde{p}$ and the true posterior $p(\boldsymbol{a}, \boldsymbol{h}, \boldsymbol{c}, \boldsymbol{g}, \boldsymbol{q} | \boldsymbol{y})$

Variational EM

Restrict solutions to the ones that allow

$$\tilde{p}(\boldsymbol{a}, \boldsymbol{h}, \boldsymbol{c}, \boldsymbol{g}, \boldsymbol{q}) = \tilde{p}_a(\boldsymbol{a})\, \tilde{p}_h(\boldsymbol{h})\, \tilde{p}_c(\boldsymbol{c})\, \tilde{p}_g(\boldsymbol{g})\, \tilde{p}_q(\boldsymbol{q})$$

E and M step can be decomposed in stages corresponding to the different parameters

The E-H step, for example, goes:

$$\tilde{p}_h = \arg\max_{\tilde{p}_h \in \mathcal{D}_H} F(\tilde{p}_a\, \tilde{p}_h\, \tilde{p}_c\, \tilde{p}_g\, \tilde{p}_q; \theta)$$

We can constraint the search to pointwise estimates $\tilde{\boldsymbol{h}}$ and $\tilde{\boldsymbol{g}}$ by replacing the probabilities on $\boldsymbol{h}$ and $\boldsymbol{g}$ by Dirac functions:

$$\tilde{p} = \tilde{p}_a\, \delta_{\tilde{\boldsymbol{h}}}\, \tilde{p}_c\, \delta_{\tilde{\boldsymbol{g}}}\, \tilde{p}_q$$

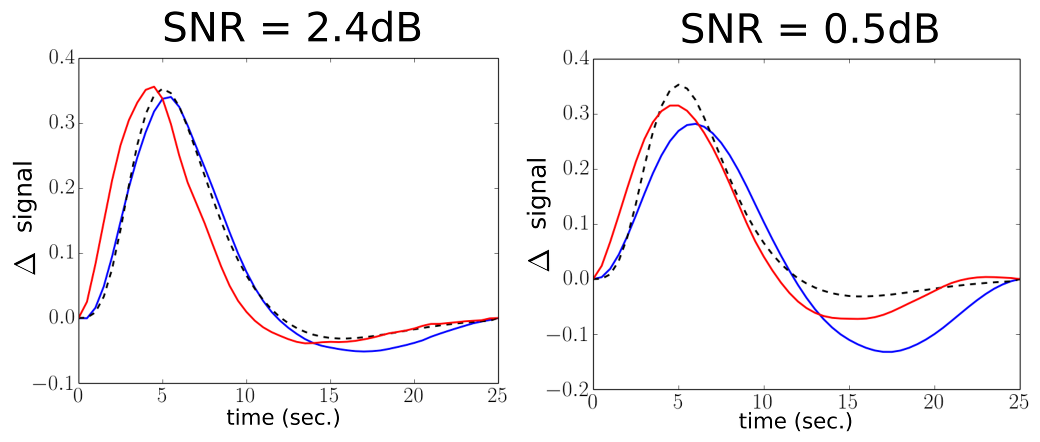
And so: $\tilde{h} = \arg\max_{\tilde{h}} F(\tilde{p}_a \delta_{\tilde{h}} \tilde{p}_c \delta_{\tilde{g}} \tilde{p}_q; \theta)$

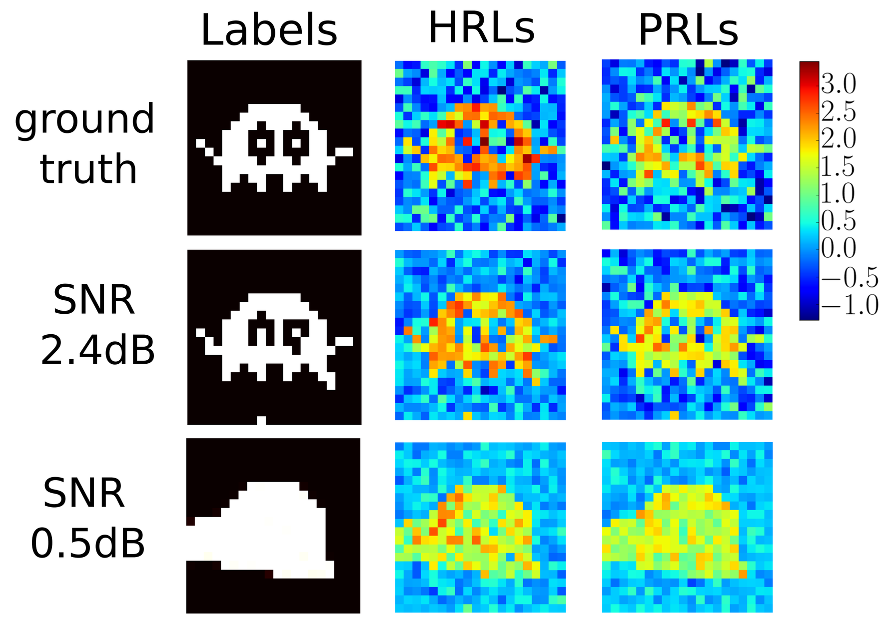
We can easily include constraints like $\|\boldsymbol{h}\|_2^2 = 1$, $\|\boldsymbol{g}\|_2^2 = 1$

Results

Artificial data

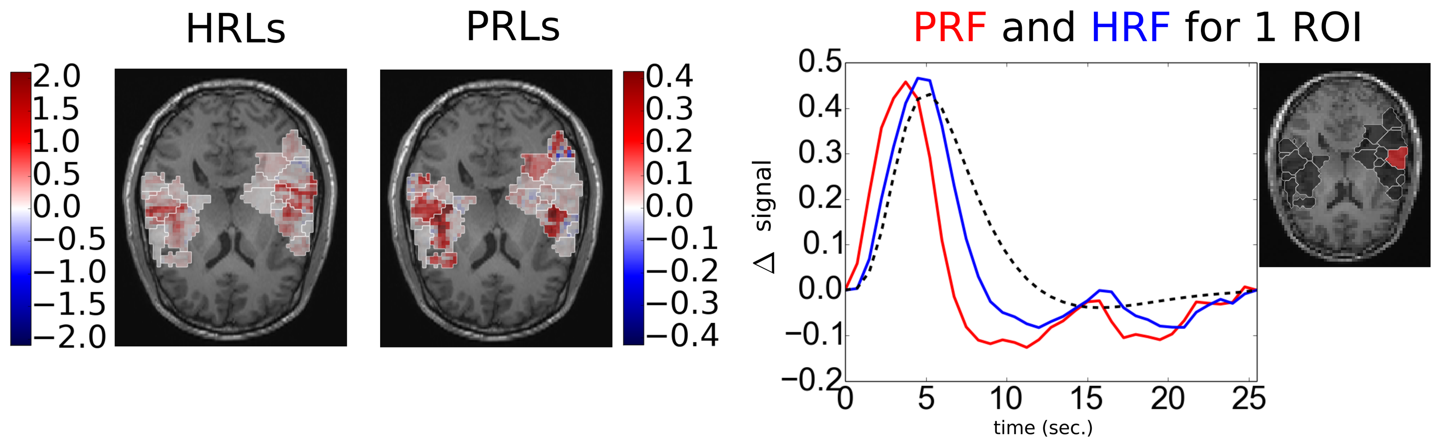
Repetition time: TR = 3s
Number of scans: 288
Fast event-related paradigm: mean ISI = 5s





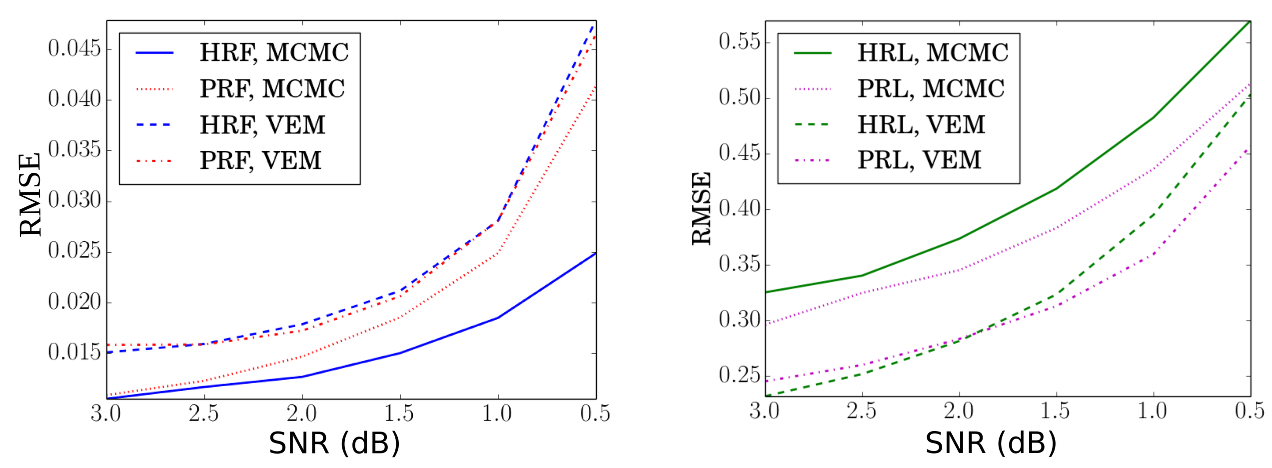
Real data

Paradigm: fast event-related design (mean ISI = 5.1s), with 60 auditory and visual stimuli, TR = 3s.



Comparison with stochastic ASL-JDE

Both methods have a similar performance, but VEM recovers better response levels while MCMC recovers better response functions



References

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