Comparison of stochastic and variational solutions to ASL fMRI data analysis

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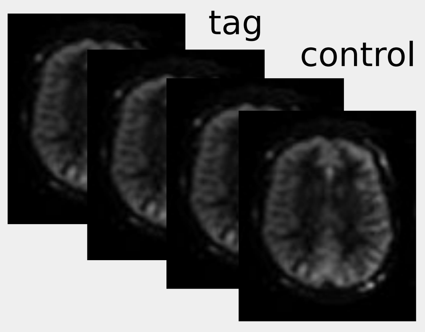
What is the problem we want to solve?

- We want to go beyond traditional BOLD fMRI analysis to extract more quantitative information about task related perfusion.
- We analyse ASL fMRI with a joint detection-estimation framework [2] that permits to estimate task-related perfusion and hemodynamic responses.

Data: Arterial Spin Labeling (ASL) [1]

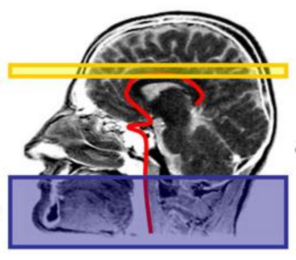
ASL fMRI provides a quantitative measurement of blood perfusion changes in the brain elicited by stimulus delivery and task performance.



Magnetically tagged image (Tag)

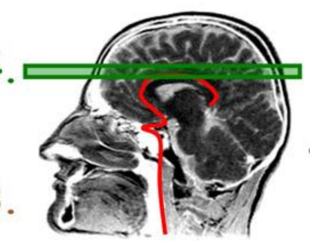
Tag inflowing arterial blood by magnetic inversion

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

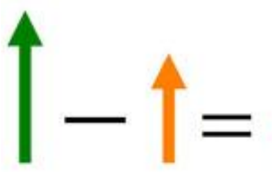


Control image

Repeat acquisition without labeling inflowing blood



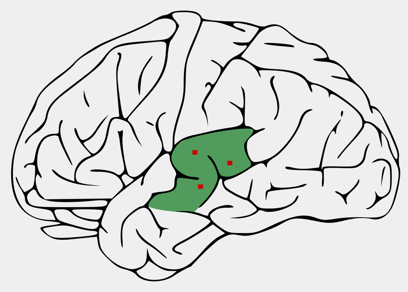
Control Image (4) - Tag Image (2)



The difference in magnetization is proportional to regional cerebral blood flow

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

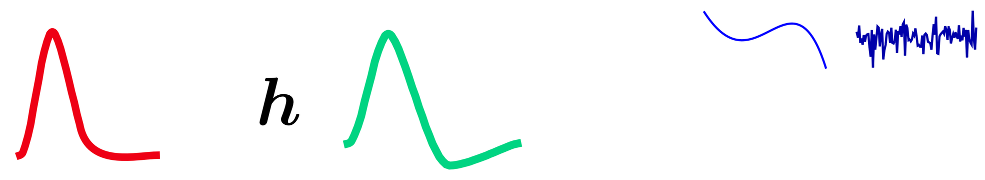
ASL signal model [2]



For every voxel in a parcel, ASL signal can be decomposed into different terms.

ASL signal = task-related perfusion + task-related BOLD + drifts and noise terms

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



parcel wise

$\boldsymbol{g}$ perfusion response function (PRF)

$\boldsymbol{h}$ hemodynamic response function (HRF)

voxel wise

$\boldsymbol{c}$ perfusion response levels (PRLs)

$\boldsymbol{a}$ hemodynamic response levels (HRLs)

$\boldsymbol{q}$ labels (active/non-active)

How do we solve it? Bayesian inference

Data: $\boldsymbol{y}$

Variables: $\boldsymbol{X} = \{\boldsymbol{a}, \boldsymbol{h}, \boldsymbol{c}, \boldsymbol{g}, \boldsymbol{q}, \boldsymbol{\theta}\}$

$$\underbrace{p(\boldsymbol{X} \mid \boldsymbol{y})}_{\text{posterior probability distribution}} \propto \underbrace{p(\boldsymbol{y}, \boldsymbol{X})}_{\text{joint prob distrib}} = \underbrace{p(\boldsymbol{y} \mid \boldsymbol{X})}_{\text{likelihood}} \underbrace{p(\boldsymbol{X})}_{\text{prior knowledge}}$$

How can we compute the posterior distribution?

Sampling: Markov Chain Monte Carlo

Gibbs sampling generates a realization of each conditional distribution at a time (of each variable in $\boldsymbol{X}$), given the current values of the other variables. *eg*: $p(\boldsymbol{a}|\boldsymbol{y}, \boldsymbol{h}, \boldsymbol{c}, \boldsymbol{g}, \boldsymbol{q}; \boldsymbol{\theta})$

- Posterior mean estimates are computed after a burn-in period.
- The sequence of samples constitutes a Markov chain, and the stationary distribution of that Markov chain is the posterior distribution.

✓ We converge to the true distribution

Approximation: Variational Expectation-Maximization

VEM approximates the posterior distribution $p(\boldsymbol{X}|\boldsymbol{y})$ by a variational distribution $\tilde{p}$ that is as close as possible to the posterior. It minimizes the Kullback-Leibler divergence $D_{\mathrm{KL}}(\tilde{p}||p(\boldsymbol{X}|\boldsymbol{y}))$

The approximation is done by restricting the solutions to the ones that satisfy $\tilde{p}(\boldsymbol{a}, \boldsymbol{h}, \boldsymbol{c}, \boldsymbol{g}, \boldsymbol{q}) = \tilde{p}_a(\boldsymbol{a})\, \tilde{p}_h(\boldsymbol{h})\, \tilde{p}_c(\boldsymbol{c})\, \tilde{p}_g(\boldsymbol{g})\, \tilde{p}_q(\boldsymbol{q})$

The E-step approximates the distribution and the M-step optimizes the hyperparameters with respect to this distribution. They can be decomposed in stages corresponding to the different parameters.

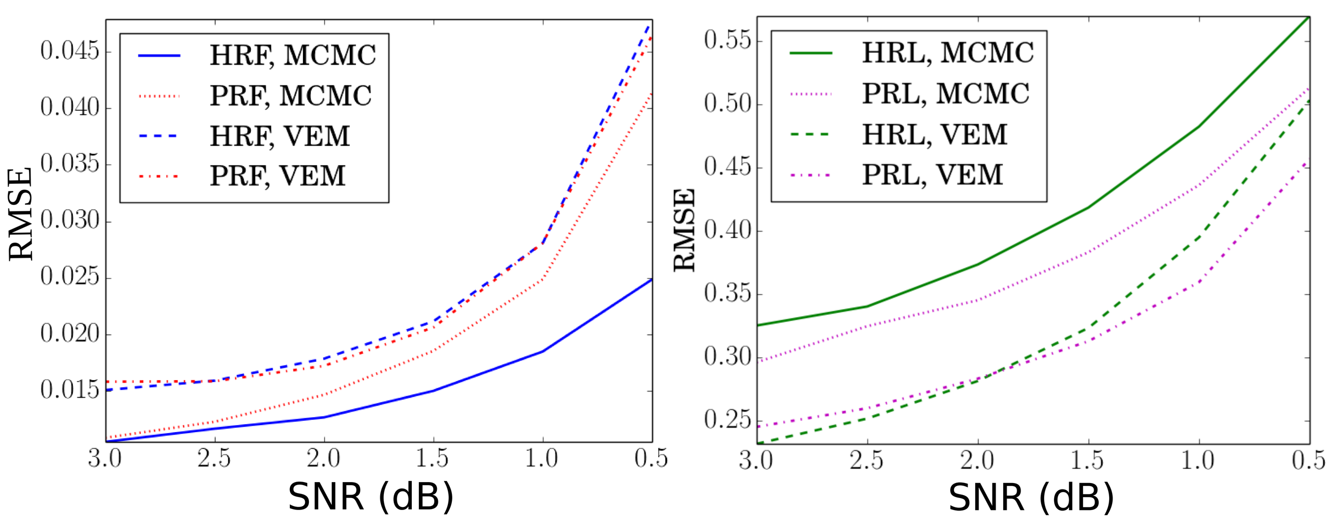
✓ Lower computational time and easy constraint handling

Results: MCMC and VEM provide comparable solutions

Artificial data

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

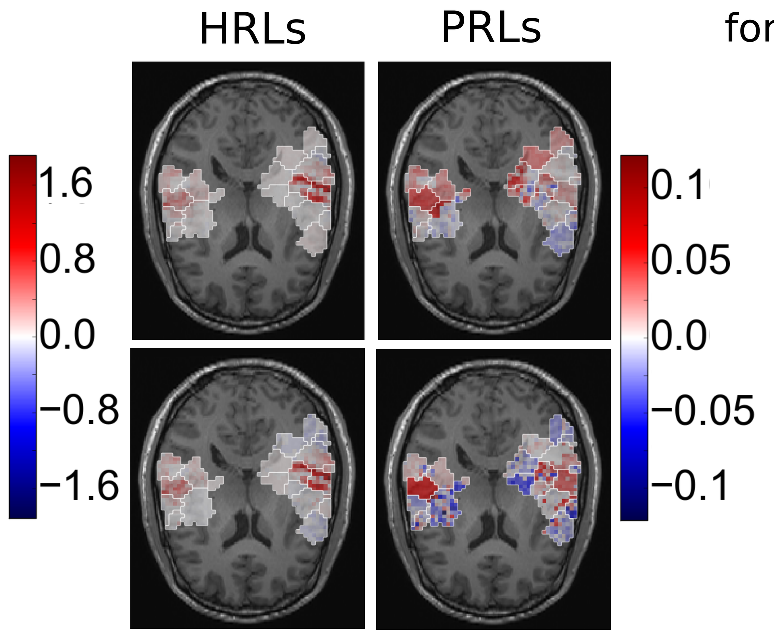
Response functions and levels RMSE error with respect to SNR

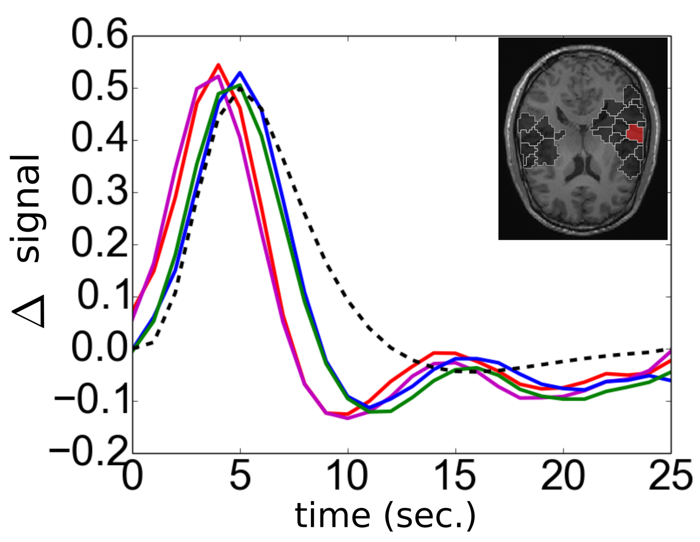


- Both methods have a similar performance, but VEM recovers response levels with a lower RMSE, while MCMC recovers response functions closer to the ground truth.

Real data

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





- Response functions are well estimated for the ROI considered.
- PRF peaks before HRF, as enforced by the physiological prior used.
- We need to find a way to better interpret the results on real data.

Computation times

Artificial data, 400 voxels

MCMC 1500 iterations
~ 270 secs
VEM 15 iterations
~ 22 secs

ratio = 12

Real data, 214 voxels

MCMC 3000 iterations
~ 320 secs
VEM 30 iterations
~ 95 secs

ratio = 3.4

Discussion

- MCMC and VEM provide good solutions for the joint estimation of the fASL signal model parameters.
- VEM provides a fast and valid alternative for fASL data analysis.
- Real data results interpretation remain unclear.

References

[1] D. Williams, J. Detre, J. Leigh, and A. Koretsky, "Magnetic resonance imaging of perfusion using spin inversion of arterial water", Proceedings of the National Academy of Sciences, vol. 89, no. 1, pp. 212–216, 1992.

[2] T. Vincent, J. Warnking, M. Villien, A. Krainik, P. Ciuciu, and F. Forbes, "Bayesian Joint Detection-Estimation of cerebral vasoreactivity from ASL fMRI data," in 16th Proc. MICCAI, LNCS Springer Verlag, Nagoya, Japan, Sep. 2013, vol. 2, pp. 616–623.