A data-driven framework for removing physiological noise in fMRI

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Introduction: physiological noise (PN) often severely limits the accuracy and reliability of measurements in functional MRI (fMRI). Pulsatile flow effects, which occur in large vessels, sinuses and ventricles, are particularly problematic; they exhibit complex signal time-courses with high variance, and are often highly correlated with experimental stimuli. Such artifacts are difficult to separate from the capillary-level haemodynamic signal. To address this issue, we have developed a procedure to estimate and control PN in fMRI data, using data-driven multivariate methods. The procedure is quantitative and data-driven, requiring no manual (and potentially subjective) identification of noise components, and performs noise estimation and removal directly from the fMRI data.

Methods: this model consists of a 2-step procedure. (1) **Down-weight contributions from large vessels and sinuses**: signal in these regions may be highly task-coupled and cannot be controlled by regression. We identify pulsatile flow regions by measuring high-frequency spectral power at each voxel, averaged over a sliding window, and adapt the high-frequency range to maximize correlation of the spectral map with an atlas of probable vessel/sinus regions (developed in-house). We then threshold the spectral map to maximize spatial overlap with the atlas, and down-weight all suprathreshold voxels by the inverse of spectral power. (2) **Optimally regress out spatially-distributed physiological noise**: for data-driven removal of physiological noise throughout the brain we have extended the PHYCAA denoising model [1] to use the spectral map of Step (1) to estimate the PN subspace while optimizing the subset of physiological noise regressors. Optimization maximises the NPAIRS metrics of model prediction accuracy and reproducibility, which do not require an activation threshold [2].

Results: Single-subject analysis results, from 20 subjects performing a Trail-Making task, are plotted as the fraction of subjects with significant activation (False Discovery Rate=0.10) at each voxel (Fig. 1). Fig. 1(*top*): without physiological correction, we observe the highest activation fractions occurring near arteries and sinuses. Fig. 1(*middle*): after spatial down-weighting, grey matter activations are consistent with prior group analyses [3]. Fig. 1(*bottom*): after optimized PN regression, fractional activations generally increase in the grey-matter regions, indicating increased spatial reliability of patterns between subjects. Figure 2 plots the changes in model reproducibility (robustness of activation maps) and prediction accuracy per subject, after performing PN regression; we observe increased metrics in 19/20 (reproducibility) and 17/20 (prediction) subjects.

Conclusion: This physiological denoising process improves prediction and reproducibility of results, and reduces the risk of signal false-positives in large vessels and sinuses. This procedure may have significant implications for studies that are highly sensitive to physiological noise, including small-sample and resting-state analyses, and studies in clinical groups.

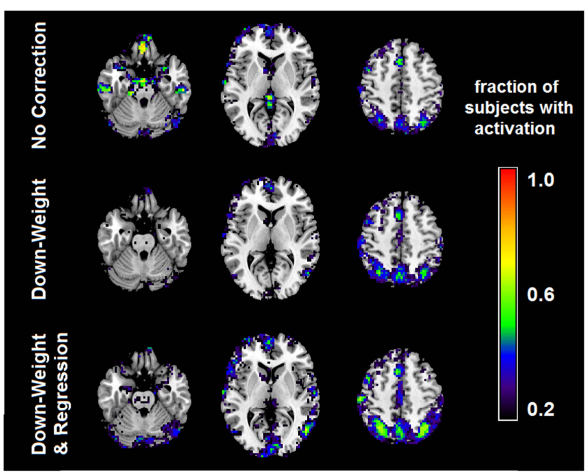

Figure 1: plot showing the fraction of subjects with activation at each voxel (FDR=0.10 threshold), across single-subject analyses.

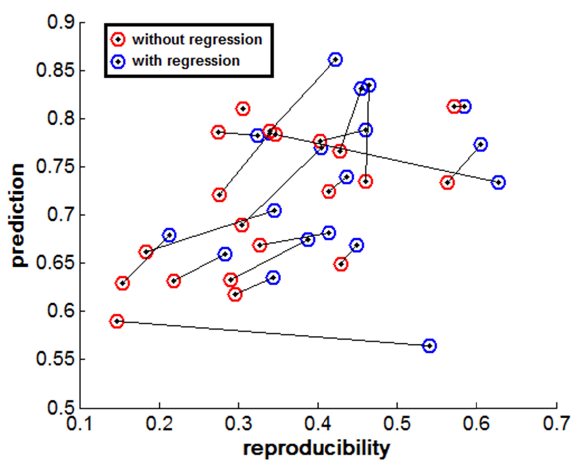

Figure 2: changes in prediction and reproducibility of single-subject analysis results, after performing physiological noise regression.

References:
[1] Churchill et al. (2011) NeuroImage doi:10.1016/j.neuroimage.2011.08.021
[2] Strother et al. (2002) NeuroImage 15(4):747-771
[3]Churchill et al. (2010) Proc. 16th Ann. Mtg. OHBM. p. 152