Quantitative General Linear Model Analysis of Arterial Spin labeling Data.
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Introduction: In an ideal quantitative perfusion FMRI experiment, the objective is to estimate the change in perfusion due to an effect of interest, as well as the baseline perfusion. Typically one would use a kinetic model to compute a perfusion image at every pair of time points (tag and control) of the series, then average together the appropriate time segments of the resulting series. Alternatively we propose to utilize the parameter estimates from a general linear model that specifies BOLD effects and ASL modulation effects. Figure 1 shows the regressors of a simple design matrix (rest and an active conditions). The first regressor and its coefficient parameter $\beta_0$ indicate the resting signal, or spin density. The second regressor describes the baseline difference between control and tagged images ($\Delta M$) $\beta_1$, is indicative of resting perfusion. The third regressor describes BOLD effect changes, and the fourth regressor describes $\Delta M$ changes due to activation. Perfusion can then be computed by translating the usual parameter estimates (1) into perfusion directly by adapting a kinetic model (e.g., see (2)) as follows:

$$f_{\text{effect}} = \lambda \beta_{\text{effect}} R_1 R_{1\text{app}} (1 - e^{-\delta / \tau})$$

where $f_{\text{effect}}$ is the perfusion change due to the effect of interest, $\alpha$ is the inversion efficiency, $\beta_{\text{effect}}$ is the parameter estimate of the regressor representing the effect of interest, $\lambda$ is the blood brain partition coefficient, $R_1$, $R_{1\text{a}}$, $R_{1\text{app}}$ are the longitudinal relaxation rates of arterial blood, tissue, and tissue in the presence of perfusion. $\delta$ is the arterial transit time, TR, $w$, and $\tau$ are repetition time, post labeling delay, and labeling duration. The same relationship can be used to derive the variance of the estimates into perfusion units.

Methods: We illustrated this technique in a working memory task, i.e. a dual N-back task with two levels of difficulty (1-back and 2-back; see (3)) was performed by a subject while being scanned with a pseudo CASL sequence (TR/TE=4000/3 ms, Tagging time=2100 ms., post inv. Delay=1500 ms. Matrix=64×64, 12 slices, thickness = 6 mm, spin-echo spiral acquisition). The subject’s performance was 98% accuracy for the 1-back task (hits minus false alarms), and 87% for the 2-back task; a performance which is in the usual range for these tasks (3). OLS analysis of prewhitened data was used to
estimate GLM parameters and to identify significantly active (Z>3) voxels. Perfusion maps were computed assuming: Transit time (δ)=1200 ms. inv. Efficiency (α) = 0.85, Gray Mater T1 = 1250 ms, Arterial T1 = 1660 ms (4,5,6,7). The significance maps were used to threshold the perfusion maps.

Results:

Figure 2 shows the resulting perfusion maps. The undelay image shows the baseline perfusion. The overlaid activations show the changes in perfusion associated with the one-back and two-back tasks. The color scales are in units of ml/min/100g. Notably, significant increases were observed bilaterally in posterior parietal cortices, and in the anterior lateral cortices. A significant decrease in perfusion is apparent in the frontal pole.

Conclusions:

GLM estimation of ASL data can yield quantitative perfusion parameter maps and their variances.

References: