

SUPPLEMENT

I. Statistical Modeling of Lobe Effects of Resting CBF

We included lobe effects on the three coefficients of nonlinear mixed effect model to test if the change of resting gray matter CBF values with age differed significantly among the four lobes.

The model can be written as follows:

$$\begin{aligned} CBF_{ij} = & \beta_0 + b_1 * I(\text{lobe} = \text{Frontal}) + b_2 * I(\text{lobe} = \text{Temporal}) + b_3 * I(\text{lobe} = \text{Parietal}) \\ & + (\beta_1 + b_4 * I(\text{lobe} = \text{Frontal}) + b_5 * I(\text{lobe} = \text{Temporal}) + b_6 \\ & * I(\text{lobe} = \text{Parietal})) \\ & * \exp\left(-\beta_2 * (\text{age}_{ij} - 6) - b_7 * I(\text{lobe} = \text{Frontal}) * (\text{age}_{ij} - 6) - b_8 \right. \\ & * I(\text{lobe} = \text{Temporal}) * (\text{age}_{ij} - 6) - b_9 * I(\text{lobe} = \text{Parietal}) * (\text{age}_{ij} - 6)\left. \right) \\ & + u_i + e_{ij} \end{aligned}$$

where $u_i \sim N(0, \sigma_u^2)$, $e_{ij} \sim N(0, \sigma_e^2)$

and

$$\begin{aligned} I(\text{lobe} = \text{Frontal}) &= \begin{cases} 1 & \text{if lobe} = \text{Frontal} \\ 0 & \text{Otherwise} \end{cases} \\ I(\text{lobe} = \text{Temporal}) &= \begin{cases} 1 & \text{if lobe} = \text{Temporal} \\ 0 & \text{Otherwise} \end{cases} \\ I(\text{lobe} = \text{Parietal}) &= \begin{cases} 1 & \text{if lobe} = \text{Parietal} \\ 0 & \text{Otherwise} \end{cases} \end{aligned}$$

Coefficients β_0 , β_1 , and β_2 reflect the mature value, change over the age range (6 to 27 years), and exponential rate constant for the occipital lobe.

Parameters b_1 to b_3 model the 3 lobe effects on the β_0 , parameters b_4 to b_6 model the 3 lobe effects on the β_1 , parameters b_7 to b_9 model the 3 lobe effects on the β_2

- 1) When we fit lobe effects on all three coefficients: β_0 , β_1 , and β_2 , only the Lobe effects on β_0 are significant ($p \leq 0.0001$ for all the lobes), i.e., all the other lobes had significant different β_0 than occipital lobe, but β_1 and β_2 were not significantly different among the lobes.
- 2) Since no significant model effects were detected with β_1 and β_2 , we dropped the lobe effects on β_1 , and fitted the model with lobe effects on β_0 and β_2 only. With this reduced model, i.e. without parameters b_4 , b_5 , and b_6 , the lobe effects were significant on both coefficients

β_0 and β_1 (for β_0 , $p < 0.0001$ for all the lobes; for β_2 , $p = 0.0088$, $p = 0.0273$, and $p = 0.0001$ for Frontal, Temporal, and Parietal, respectively).

- 3) Then we dropped the lobe effects parameters on β_2 , and fitted the model with lobe effects on β_0 and β_1 only. With this reduced model, i.e. without parameters b_7 , b_9 , and b_9 , the lobe effects were significant on both coefficients β_0 and β_1 (for β_0 , $p < 0.0001$ for all the lobes; for β_2 , $p = 0.0241$, $p = 0.0317$, and $p = 0.0017$ for Frontal, Temporal, and Parietal, respectively).

II. Statistical Modeling with Gender Effects

For the linear mixed-effect age models, the gender effects were added as:

$$y_{ij} = \beta_0 + \beta_1 * age_{ij} + b_1 * gender_i + b_2 * (gender_i * age_{ij}) + u_i + e_{ij}$$

where $gender = 0$ (female) or 1 (male), $u_i \sim N(0, \sigma_u^2)$, $e_{ij} \sim N(0, \sigma_e^2)$, i denotes the i^{th} subject and j denoted the j^{th} measurement for the i^{th} subject.

Coefficients β_1 is the age effect; parameter b_1 reflects the gender effect, and b_2 reflects age gender interaction effect.

For the nonlinear mixed-effect age models, the gender effects were added as:

$$y_{ij} = \beta_0 + b_0 * gender + (\beta_1 + b_1 * gender) * \exp(-(age_{ij} - 6)/\beta_2 - b_2 * gender - b_3 * age_{ij} * gender) + u_i + e_{ij}$$

where $gender = 0$ (female) or 1 (male), $u_i \sim N(0, \sigma_u^2)$, $e_{ij} \sim N(0, \sigma_e^2)$, i denotes the i^{th} subject and j denoted the j^{th} measurement for the i^{th} subject.

Coefficients β_0 , β_1 , and β_2 , reflect the mature value, total change over the age range (6 to 27 years), and exponential rate constant (rate of change per year). Parameters b_0 , b_1 , and b_2 are the gender effects on β_0 , β_1 , and β_2 ; parameter b_3 is the age gender interaction effect for the model.

III. Estimate of the Coupling Parameter k

A heuristic model (Simon et. al., 2013) links changes in CBF (f) to changes in BOLD signal (b) as:

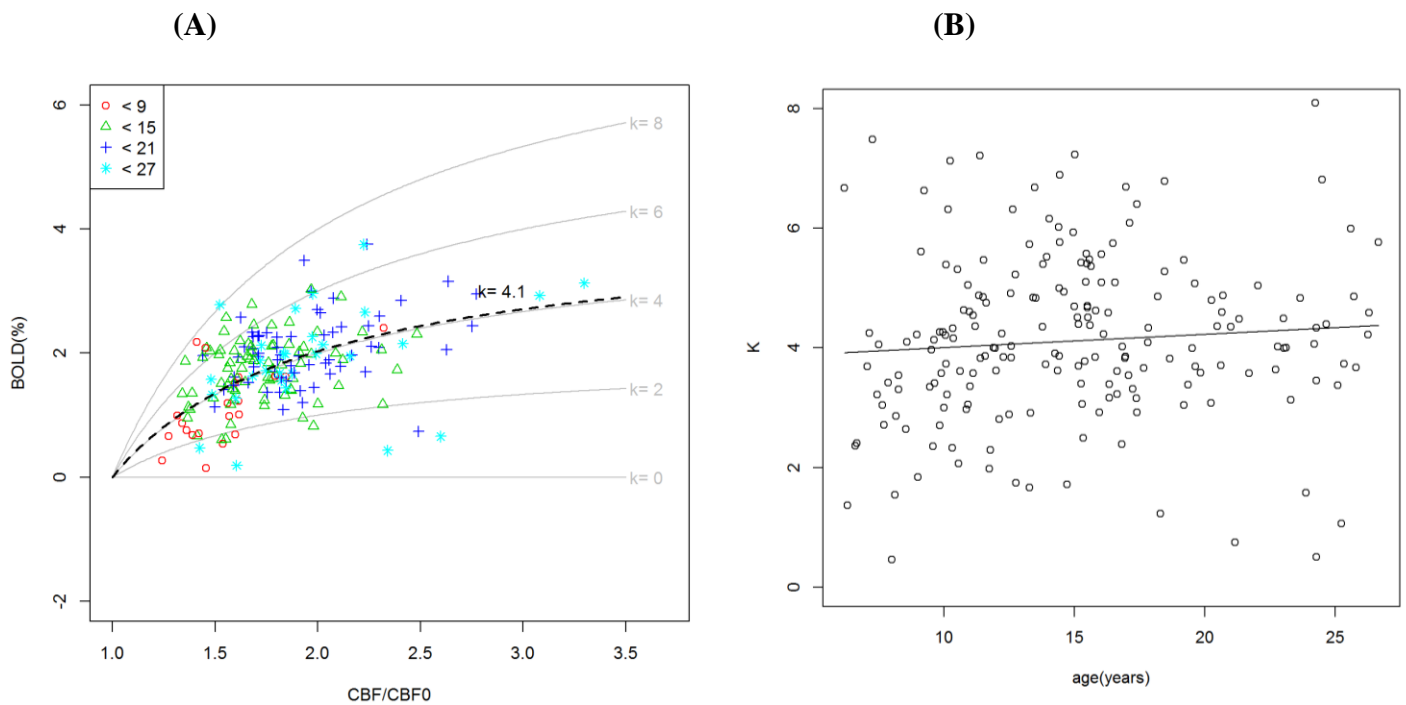
$$\frac{b(t)-b_0}{b_0} = M(1 - \alpha_v - \lambda) \left(1 - \frac{f_0}{f(t)}\right) = k \left(1 - \frac{f_0}{f(t)}\right)$$

where M is a scaling factor related to imaging parameters and baseline physiological factors; α_v , is the power law exponent (Grubb's constant) relating CBV (V) to CBF ($V = f^{\alpha_v}$); and λ is the CMRO₂/CBF coupling ratio ($\lambda = \frac{\Delta CMRO_2 / CMRO_{20}}{\Delta CBF / CBF_0}$). These 3 unknown parameters can be combined into a single factor k , which is an apparent coupling parameter that scales BOLD signal to a nonlinear function of CBF change. We estimated the k parameter using the complete time courses of CBF and BOLD for each subject and tested age-effects on k with a linear mixed-effect model:

$$k_{ij} = \beta_0 + \beta_1 * age_{ij} + u_i + e_{ij}$$

where $u_i \sim N(0, \sigma_u^2)$, $e_{ij} \sim N(0, \sigma_e^2)$, i denoted the i^{th} subject and j denoted the j^{th} measurement for the i^{th} subject.

The estimated k values and its relation to age are plotted below.



(A) Scatter plot of peak BOLD (%) signal vs. fractional CBF changes. Data were color coded to reflect age groups for each participant. (B) Fitted k values vs. age. No significant age effect ($p = 0.84$) was detected for k .

- Simon, A.B., Griffeth, V.E., Wong, E.C., Buxton, R.B. (2013) A novel method of combining blood oxygenation and blood flow sensitive magnetic resonance imaging techniques to measure the cerebral blood flow and oxygen metabolism responses to an unknown neural stimulus. PloS one, 8:e54816.