Age prediction with physiologically-induced resting-state fMRI BOLD variability

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Background

- The temporal variability of blood oxygen level-dependent (BOLD) signal changes has been shown to be a good predictor of age[1]
- Physiological factors like respiratory variation (RV) and heart rate (HR) contribute to BOLD signal independently of neural activity by introducing alternations in cerebral blood flow, cerebral blood volume and arterial CO_2 concentration[2, 3].
- While typically regarded as noise, RV and HR may contribute important information about brain physiology in aging. Further, the degree to which previously reported age-related changes in BOLD variability arises from physiological factors is unknown.
- Here, we investigated the relationship between the fMRI physiological component and age by exploring whether physiologically-induced fMRI BOLD variability is predicative of age, on both voxel and ROI level.

Dataset

- We included the 3T resting-state fMRI scans of 515 subjects from the Nathan Kline Institute Rockland Sample [4] with an age range of 19 - 85 years old (voxel size = 2*2*2 mm and TR = 1400 ms).
- The preprocessing steps included 1) motion correction in FSL, 2) nonlinear registration into the MNI152 space with ANTS, 3) spatial smoothing with a 3.0mm FWHM Gaussian kernel, and 4) regressing out the linear and quadratic trends in the time courses in AFNI.
- RV is represented as the standard deviation (SD) of a sliding window of 6 s centered at each TR. Similarly, HR is extracted by calculating the inverse of the mean inter-beat-interval in the 6 s-long sliding windows around each TR.

References

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Results

- An average Pearson Correlation Coefficient (PCC) of 0.68 between the predicted age and target age was achieved with the voxel-based analysis with SVR using linear kernel.
- For the ROI-based analysis, an average PCC of 0.57 was achieved using linear kernel, and an average of 0.63 was achieved using RBF nonlinear kernel.
- The permutation test was carried out by randomly selecting another subject's physiological recording to derive the fMRI RVHR component (both voxel- and ROI-based), and using the same SVR models to do the age prediction 100 times with the same 5-fold split.

	Kernel	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean
Voxel	Linear	0.72	0.67	0.68	0.65	0.68	0.68**
ROI	Linear	0.56	0.49	0.63	0.61	0.55	0.57**
	RBF	0.57	0.66	0.67	0.65	0.61	0.63**

** Result is significant compared to the null distribution generated by the permutation test with p<0.01

Table 1. Age prediction result using SVR across the same 5 test sets. The values shown in the table are the Pearson Correlation Coefficient (PCC) between the predicted age and target age.

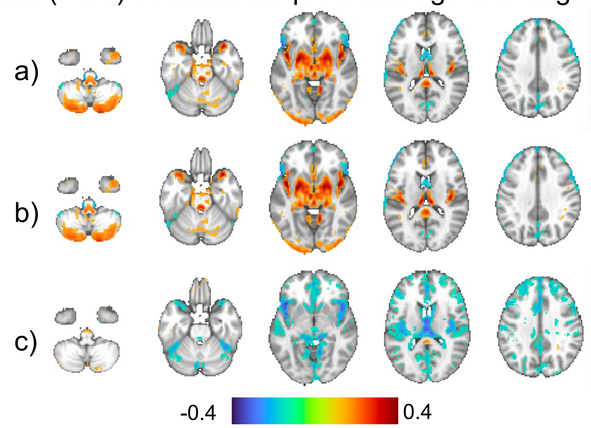

Figure 1. Correlation patterns between age and a) voxelwise fMRI variability (percent signal change), b) voxelwise fMRI variability (percent signal change) with the removal of RVHR component, and c) voxelwise fMRI RVHR component variability after controlling for the subject's sex, ethnicity, race, native language, height, weight, BMI and pulse. The correlation values have been FDR (false discovery rate) corrected using a q-value of 0.01.

Method

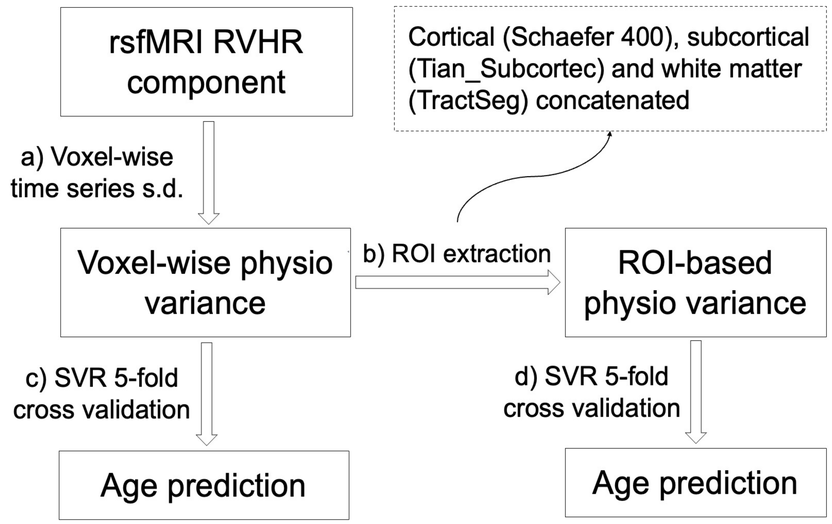

Figure 2. Flowchart of the age prediction process. The combined RV and HR ("RVHR")-induced fMRI is extracted from the z-scored fMRI signal using a least-squares fit, with the basis functions proposed by Chen et al..[5] a) The RVHR-induced fMRI variance map was then calculated by taking the SD of the voxelwise fMRI RVHR time series. b) ROI-based RVHR variance maps were computed by taking the average of the SD within ROIs. c, d) Support vector regression (SVR) model is used to perform age prediction with voxel/ROI-based fMRI variance maps.

Conclusion and Future Steps

- Our finding suggests that the fMRI physiological component is indicative of age and contains useful information regarding aging-related brain hemodynamic changes.
- We would like to model how different brain regions' RVHR BOLD variances change across the lifespan. In addition, we are interested in how RVHR fMRI is related to cognitive measures. Furthermore, we want to explore how different normalization strategies or variance metrics affect the age prediction results.