Boosting Hyperalignment Performance with Age-specific Templates

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Abstract

The brain undergoes significant developmental and functional changes over the lifespan, and certain features in brain functional organization may be more prominent in certain age groups than others. Due to individual differences in functional–anatomical correspondence, features encoded in fine-grained spatial patterns need to be functionally aligned using hyperalignment. In this work, we examine whether age-specific functional templates improve hyperalignment. We built age-specific templates using the Cambridge Centre for Ageing and Neuroscience (Cam-CAN) dataset (18–87 yo) and evaluated their performance. We found that congruent age-specific templates improve the performance of (a) predicting individualized connectomes, (b) predicting individualized brain responses during movie watching, and (c) inter-subject correlation of connectivity profiles. This work enhances our understanding of age-related differences in brain function, highlights the benefits of creating age-specific templates to refine hyperalignment model performance, and may contribute to the development of age-sensitive diagnostic tools and interventions for neurological disorders.

Keywords: fMRI, hyperalignment, brain aging, individual differences, functional connectivity

Introduction

Different brains encode the same information as idiosyncratic spatial patterns. As a result, information encoded in fine-grained spatial patterns cannot be aligned using anatomical alignment (Cox & Savoy, 2003; Haxby et al., 2001, 2014). Connectivity hyperalignment (CHA) solves this by projecting brains into a common connectivity space that preserves both coarse and fine detail (Guntupalli et al., 2018; Haxby et al., 2011, 2020), enhancing sensitivity to individual differences (Feilong et al., 2018, 2021).

In this work, we investigated whether incorporating age-specific templates enhances the performance of hyperalignment models. Our results indicate that congruent templates (i.e., constructed using data from the same age group) enhance inter-subject correlation (ISC) of functional connectivity and prediction accuracy of individual connectomes compared to incongruent templates.

Predicting individualized connectome

We classified the participants into three different age groups—young, mid, and old—with each group consisting of around the same number of people. Our analyses focused on the young and old groups. For each age group, we built the templates using two thirds of the participants (~144) and withheld the remaining one third for testing (~72). For each participant, we used independent data for training hyperalignment and evaluating performance (Figure 1).

For each individual, we calculated the correlation between the predicted connectome, generated using different age group hyperalignment templates, and the measured connectome, calculated using movie watching fMRI data. A higher correlation indicates a more accurate prediction, which means better performance of the hyperalignment template.

We compared the performance of congruent and incongruent templates on Cam-CAN participants (Taylor et al., 2017). Congruent templates perform better than incongruent templates for both age groups (Figure 2a), and we observed the advantage in almost all participants (Figure 2b; 98.6% in the young group and 94.4% in the old group). The advantage of congruent templates is most prominent in frontal and parietal lobes (Figure 2c)—regions primarily responsible for cognitive functions—which can be significantly influenced by age.

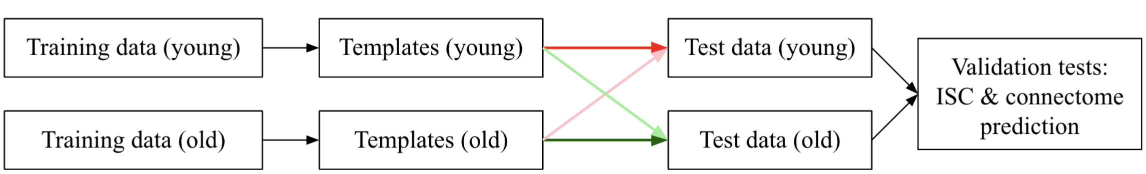

Figure 1: Schematic of the procedure for building and testing hyperalignment templates.

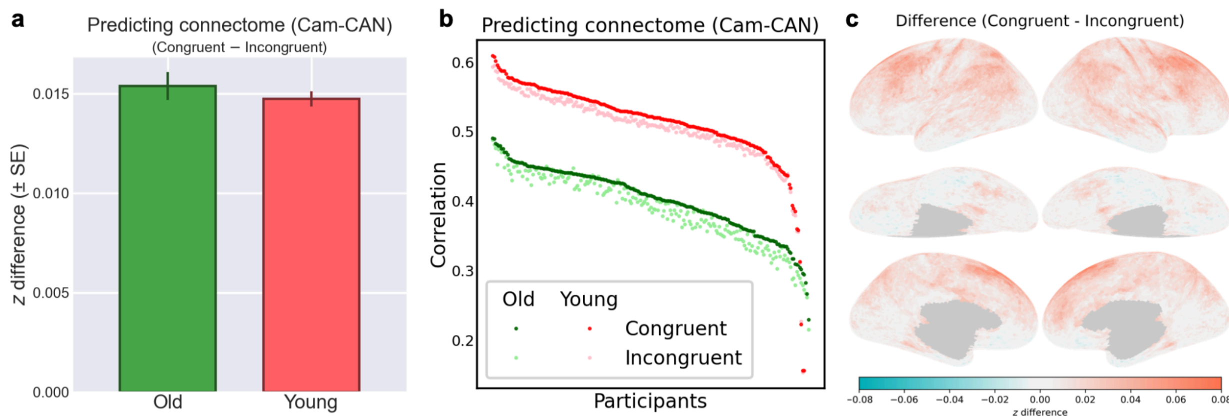

Figure 2: Comparison of prediction performance between congruent and incongruent templates.

To evaluate the influence of age on the performance of hyperalignment template across the entire lifespan, we computed the correlation between actual connectome and predicted connectome of all participants using both young templates and old templates. As an individual's age becomes more distant from the template age group, the relative performance of the template decreases (Figure 3).

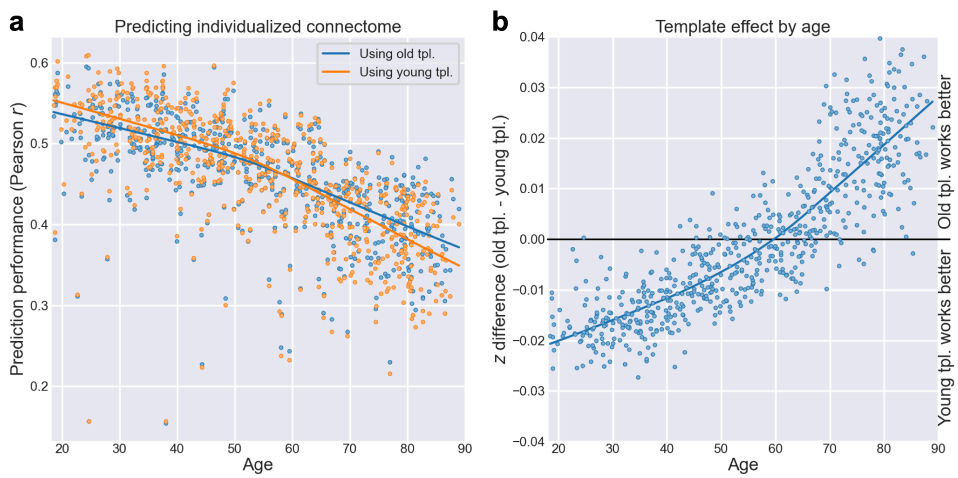

Figure 3: Performance difference between young and old templates for individuals across all age spans.

Additional Validation Analyses

We extended the original analysis and demonstrated that congruent age-specific templates predict neural responses to the movie better than incongruent templates. We also found that inter-subject correlations (ISCs) of connectivity profiles based on congruent templates were higher than incongruent ones, for both the Cam-CAN dataset and the Dallas Lifespan Brain Study (DLBS) dataset. These results demonstrate that congruent age-specific templates outperforms incongruent ones across datasets and metrics.

Conclusion

In this paper, we analyzed the effect of age on hyperalignment performance and demonstrated the advantage of age-specific hyperalignment templates on predicting individualized connectomes, predicting brain response prediction during movie watching, and ISC of connectivity profiles. This approach could provide insights into the pathophysiological mechanisms underlying various clinical conditions and broaden the use of hyperalignment models in clinical neuroscience.

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