Computational study of changes to cortical vision with age

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Background

In recent years, many studies have linked popular models in computer vision to cortical responses in mid- to high-level visual regions of the brain. Convolutional neural networks (CNNs) are currently the models of choice, showing significant predictions from V1 to inferotemporal cortex (e.g., Horikawa 2017, Cichy 2016). However, the **visual properties underlying the connection between computer model and cortical representations remain uncertain**. Furthermore, nearly all neuroimaging data in recent visual modeling studies comes from subjects aged 20 to 40 years old, omitting substantial adult populations. **Almost no work has been done to model potential variability of cortical visual representations with age**, particularly beyond early vision (Brewer 2014, Chang 2015).

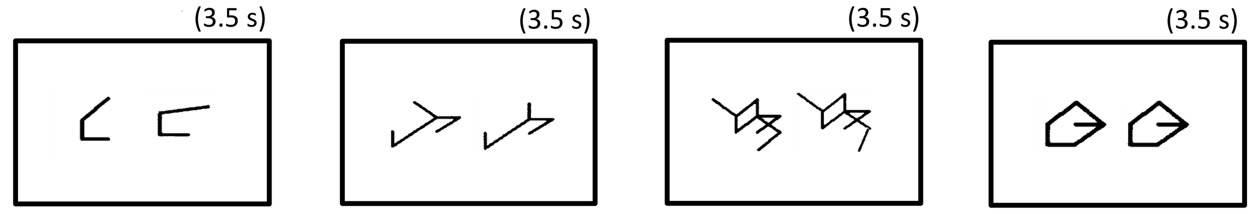
Studies with CNNs and other cortically-linked computational models indicate an importance of shape for higher level visual representation (Kubilius 2016, Leeds 2014). The Shock Graph/Medial Axis model provides a more compact and straight-forward computational representation of shape, also shown to capture cortical visual responses (e.g., Leeds 2013, Lescroart 2013). **We explore cortical shape perception through the use of the Shock Graph model**.

Within young adults, substantial inter-subject variability has been observed in which computational visual models predict cortical responses in which visual regions (Leeds 2013). To understand age-based subject variability in cortical perception, **we explore cortical activity of subjects from 20 to 80 years old while engaged in a simple visual task**. We also explore changes in cognitive ability concurrent with changes in visual representations.

Methods: Pattern matching study

Neuroimaging and behavioural data from Stern (2014)

Studied **32 subjects – 16 20-40 years, 16 60-80 years**, no psychiatric conditions or cognitive impairment
Each subject viewed 60 pairs of line patterns while in the fMRI scanner.
Subjects indicated whether the two patterns were the same or different with a differential button press.
Block design – 3.5 s ITI; 5 task blocks of 17s each

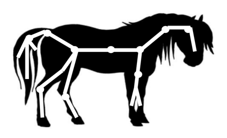


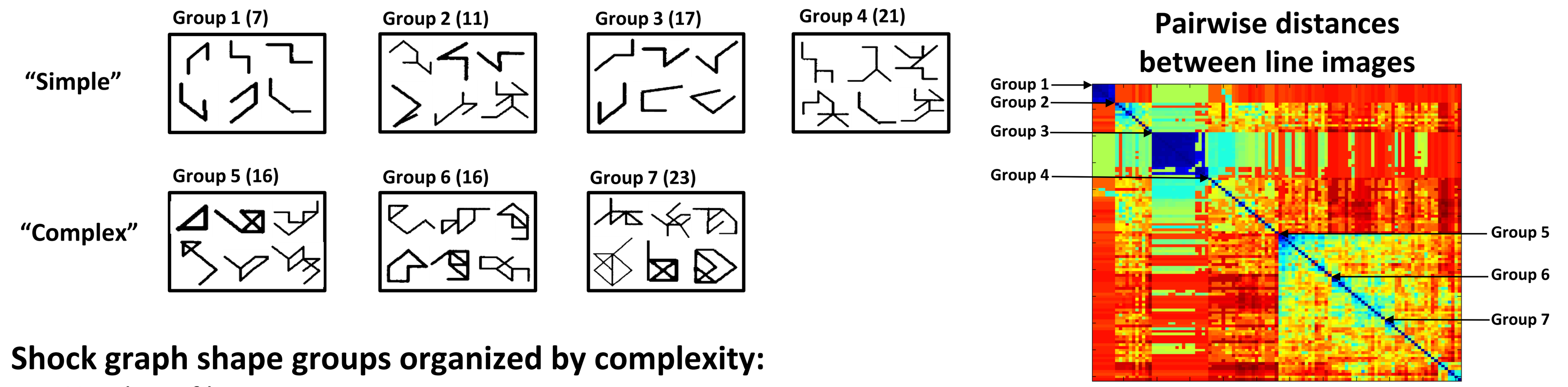
2x2x3mm voxels; 2 s TR, full-brain coverage

Computational shape model

The **Shock Graph** model is used to create a **representation of visual object shape** through a construction of an enhanced medial axis skeleton of the image (e.g., Siddiqi 1999).

111 line images from Stern pattern comparison task compared by graph matching and grouped through hierarchical agglomerative clustering.





Shock graph shape groups organized by complexity:

- Number of line segments
- Open/closed shapes

- Higher in-group homogeneity for groups 1-3
- Higher cross-group similarities for groups 5-7

Results: Task-specific regions

Analysis

Create predicted hemodynamic response: fit triangular HRF for each trial onset

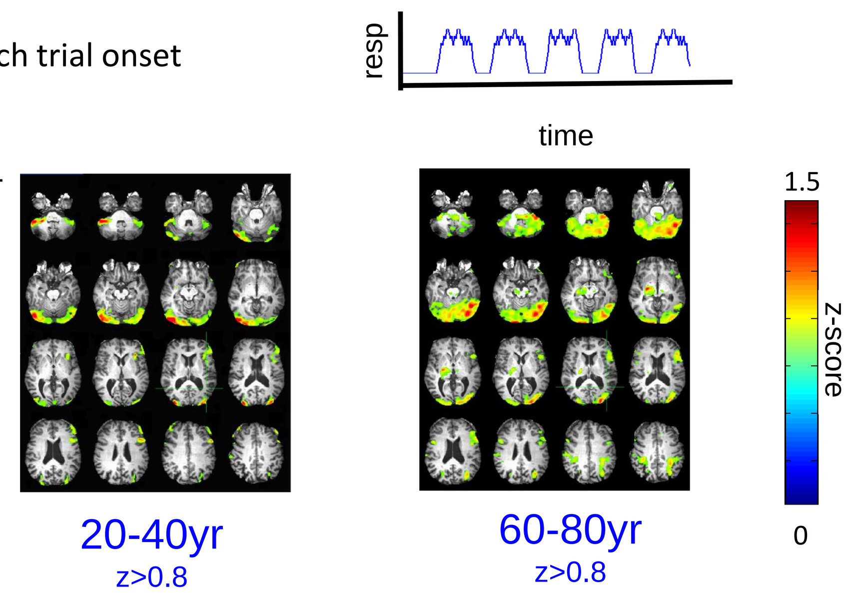
For each voxel, correlate model and cortical response

Compute z-score of correlations across subjects: $z = \frac{\mu_{responseCorr}}{\sigma_{responseCorr}}$

Findings

High differential activity in **early-to-mid level vision** regions and motor/action regions

60+ yr subjects show broader span of task-specific regions, centered around same locations as 40- yr subjects



Results: Stimulus specific regions (two-group comparison)

Analysis, by age

Create predicted hemodynamic responses: based on onset of at least one pattern from desired group

For each voxel, correlate model and cortical responses only during task blocks

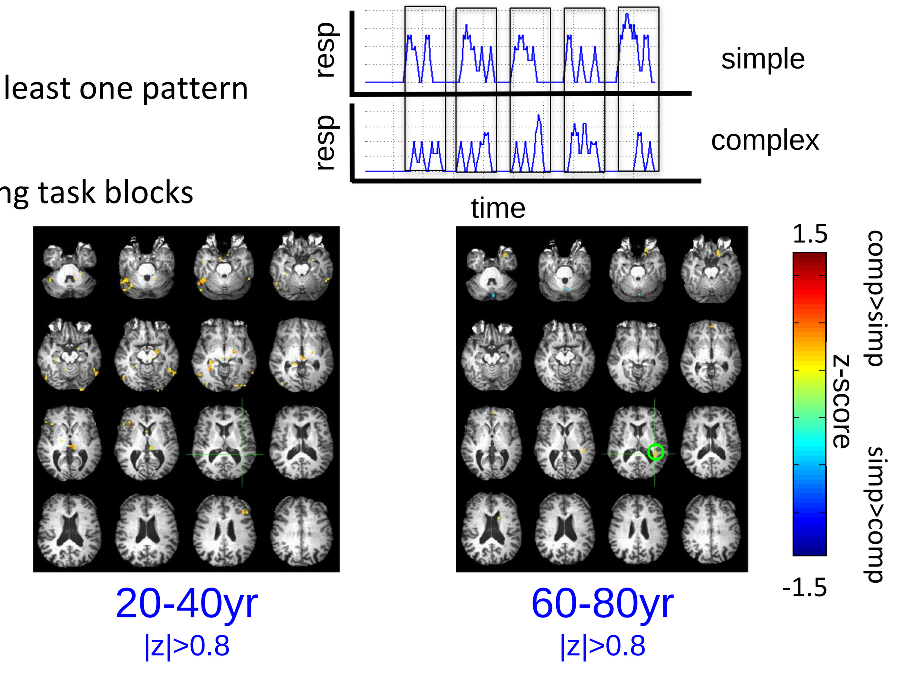
Find $diff = corr_{complex} - corr_{simple}$ at each voxel

Compute z-score of *diff* across subjects

Findings

40- yr subjects show heightened correlation in early/mid-level vision for "complex" group as well as motor/executive regions

60+ yr subjects show heightened correlation in limited regions of MTG for "complex" group



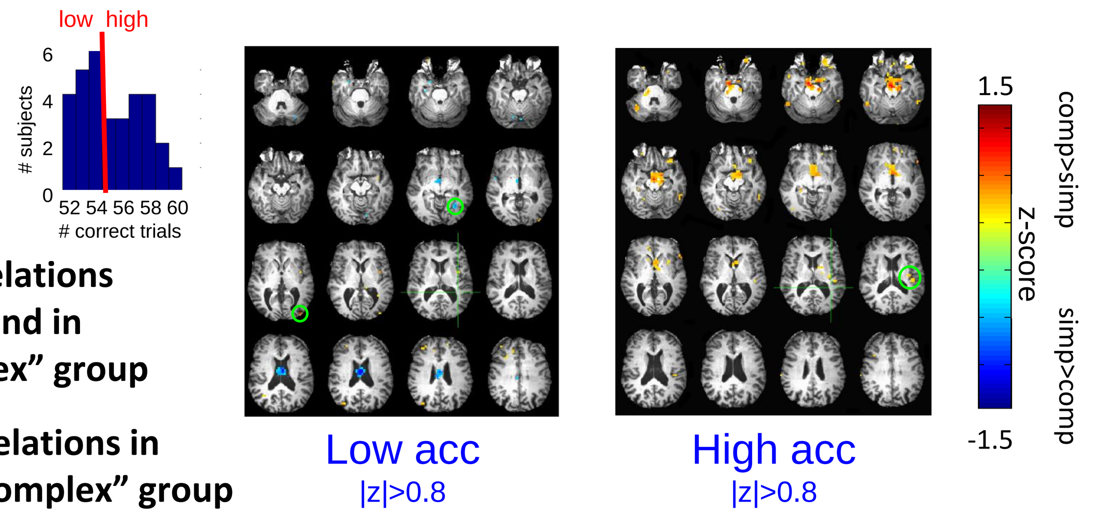
Group-specific regions, by accuracy

Split subjects based on number of correct trials
≤54 "low accuracy" >54 "high accuracy"

Findings

Low accuracy subjects show heightened correlations in limited regions of PHC for "simple" group and in limited regions of dorsal pathway for "complex" group

High accuracy subjects show heightened correlations in limited mid-level ventral visual regions for "complex" group as well as motor/executive regions



Results: Stimulus-specific regions (seven-group comparison)

Analysis

Similar to two-group comparison
Each predicted response for stimuli in one of the seven shape groups
Compare voxel responses for pairs of groups: $diff = corr_{GroupI} - corr_{GroupJ}$ where $I \neq J$

Findings

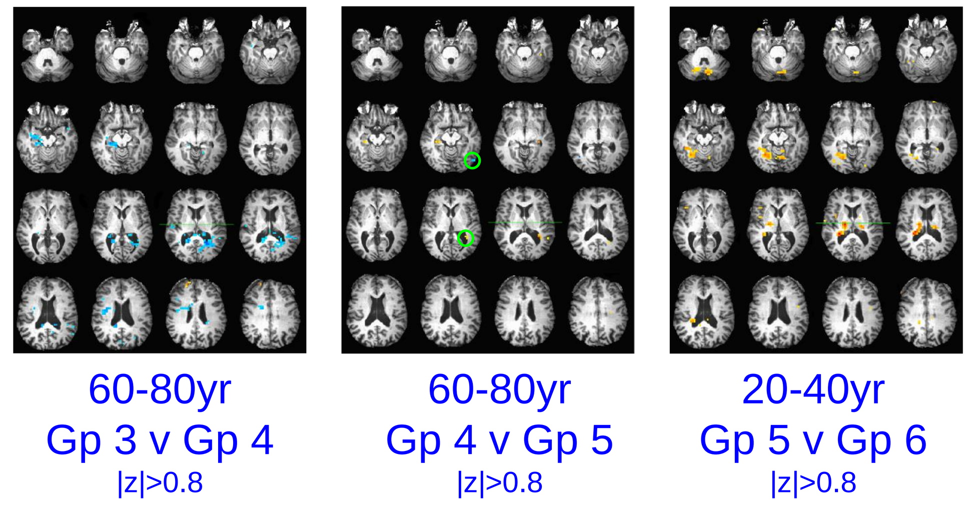
For most group pairs, no strong differences in correlations

By Age

60+ yr subjects: higher corrs in limited PHC regions for group 3 and in executive/motor regions

60+ yr subjects: higher corrs in limited PHC regions for group 5

40- yr subjects: higher corrs in Fus for group 6

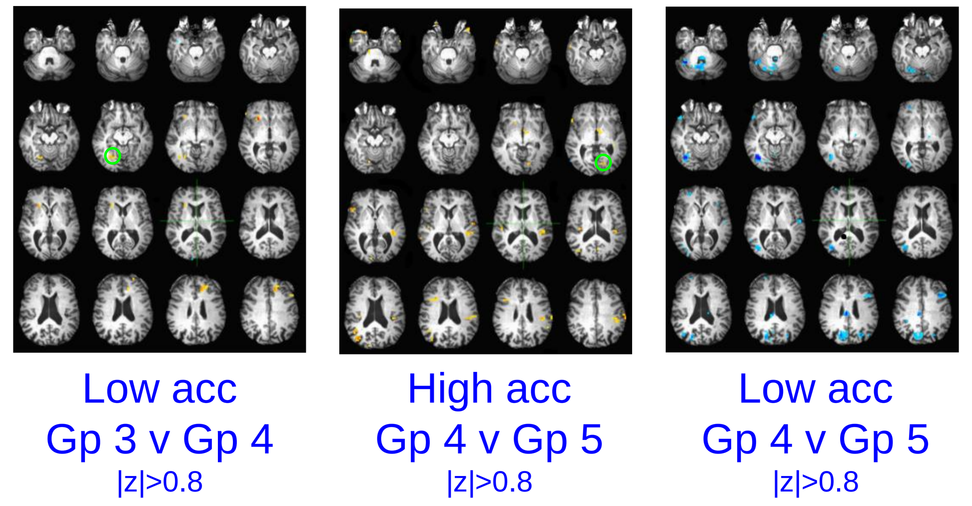


By Accuracy

Low acc subjects: higher corrs in limited Fus regions for group 4 and in executive/motor regions

High acc subjects: higher corrs in limited mid-level visual regions for group 5 and in executive/motor regions

Low acc subjects: higher corrs in mid-level visual regions for group 4



Discussion

Summary of findings:

- Different shape classes captured by shock graphs show differential effects on cortical activity inside and outside regions associated with vision.
- Shape effects on cortical activity change with age and with cognitive performance.
- Motor/executive regions affected by shape differentially by age/cognitive performance.

Future directions:

- Expand study to further subjects under 40, above 60, and between 40 and 60.
- Employ more natural stimuli.
- Explore CNN matches to cortical activity by age/cognitive performance

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