Mixing hierarchical edge detection and medial axis models of object perception

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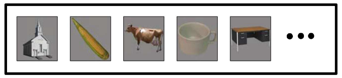
Diverse models of cortical perception

- Multiple potential frameworks have been proposed to characterize cortical object perception
- Prominent models capturing holistic shapes and local-features show promise accounting for cortical responses to visual objects (Leeds 2013; Hung 2012; Yamins 2014)
- We show mixing holistic Shock graph and local-features SIFT models sometimes – but not always – provides a better account of cortical activity than does either model alone

Methods

- Participants shown photos of 60 real-world objects, 6 x each, passive viewing

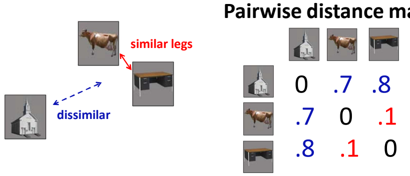


- BOLD signals recorded with slow event-related design (2 sec TR, partial coverage) for 5 subjects

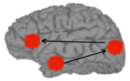
Representational dissimilarity analysis

- Representational dissimilarity: use pairwise distance matrix to show how stimuli are grouped by each neural and computational representation

Pairwise distance matrix



- **Neural:** 123-voxel sphere of responses at each location



- **Computational models:**
  - SIFT – bag of multi-scale Gabor-based visual words (similarities to Convolutional Neural Nets)
  - Shock graph – enhanced medial axis

- **Neural vs model comparison:** Spearman correlation between elements of neural and model distance matrices (Leeds 2013)

Joint SIFT/Shock graph model

Investigate contributions of each model to explain neural groupings (neural distance matrices) with **linear**, **bilinear**, and **quadratic** terms

Find $c_1, \ldots, c_6$ to best-fit

$$\text{neural}(i,j) \approx \boxed{\begin{aligned}\text{combine}(i,j) = c_1 + c_2\,\text{SIFT}(i,j) + c_3\,\text{Shock}(i,j)\\ + c_4\,\text{SIFT}(i,j)\,\text{Shock}(i,j)\\ + c_5\,\text{SIFT}(i,j)^2 + c_6\,\text{Shock}(i,j)^2\end{aligned}}$$

for each pair of stimuli *(stim$_i$, stim$_j$)*

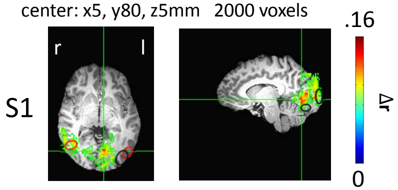
Find $r^{combine}$=corr(**neural**, **combine**)

Correlation increases from joint model

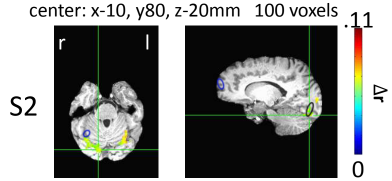
LOC localizer SIFT only Shock graph only Joint region center

q<1e-4 $\Delta r = r^{combine}-\max(r^{sift}, r^{shock})$ *via permutation test*

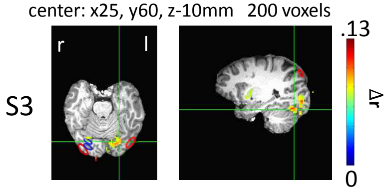
center: x5, y80, z5mm 2000 voxels



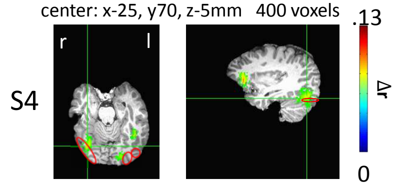
center: x-10, y80, z-20mm 100 voxels



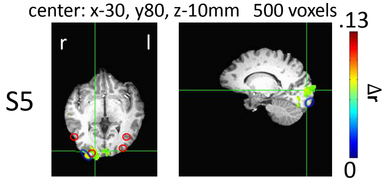
center: x25, y60, z-10mm 200 voxels



center: x-25, y70, z-5mm 400 voxels



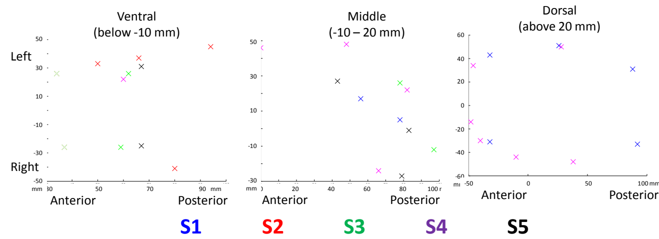
center: x-30, y80, z-10mm 500 voxels



Largest region of joint model correlation increase

- In medial occipital lobe
- Span 5-15 mm^3 volume
- Vary in overlap with LOC localizer
- Low overlap with regions of top SIFT and Shock correlations
- Provide 50-100% increase in match above single model (from r=.1 to r=.2)

Distribution of centers for regions of correlation increase

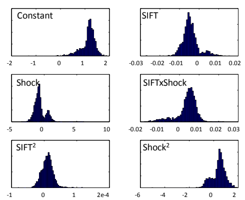


Centers are located

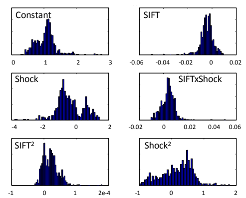
- Bilateral
- Posterior ventral (+ dorsal)
  - Inferior occipital
  - Fusiform
  - Lateral occipital
  - Lingual gyrus
  - Superior parietal
- Anterior dorsal
  - Prefrontal cortex
  - Smaller regions

Joint coefficients for increased correlation

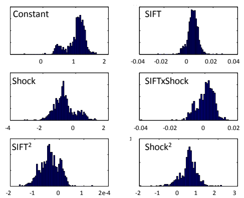
S1



S2



S4



- Typically 1-2 common coefficients per combination-model term
- Typically ~1 standard deviation away from 0
- Typical scale (-10 to 10 or -0.01 to 0.01) and values per combination-model term across subjects

Discussion

- **Non-linear combination of diverse models better accounts for voxel responses** in subset of mid- and high-level visual areas
- When combination provides true improvement, best fit **combination coefficients fairly consistent** across subjects and regions
- **Future directions:**
  - Expand to Convolutional Neural Networks
  - Expand to further non-linear model combinations

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Acknowledgments

Fordham University Faculty Research Grant; **Pennsylvania Department of Health**'s Commonwealth Universal Research Enhancement Program, **NIH** EUREKA Award #1R01MH084195A01, and the Temporal Dynamic of Learning Center at UCSD (NSF Science of Learning Center #SMA-1041755)