Quantifying the role of perceived curvature in the processing of natural object images

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BACKGROUND

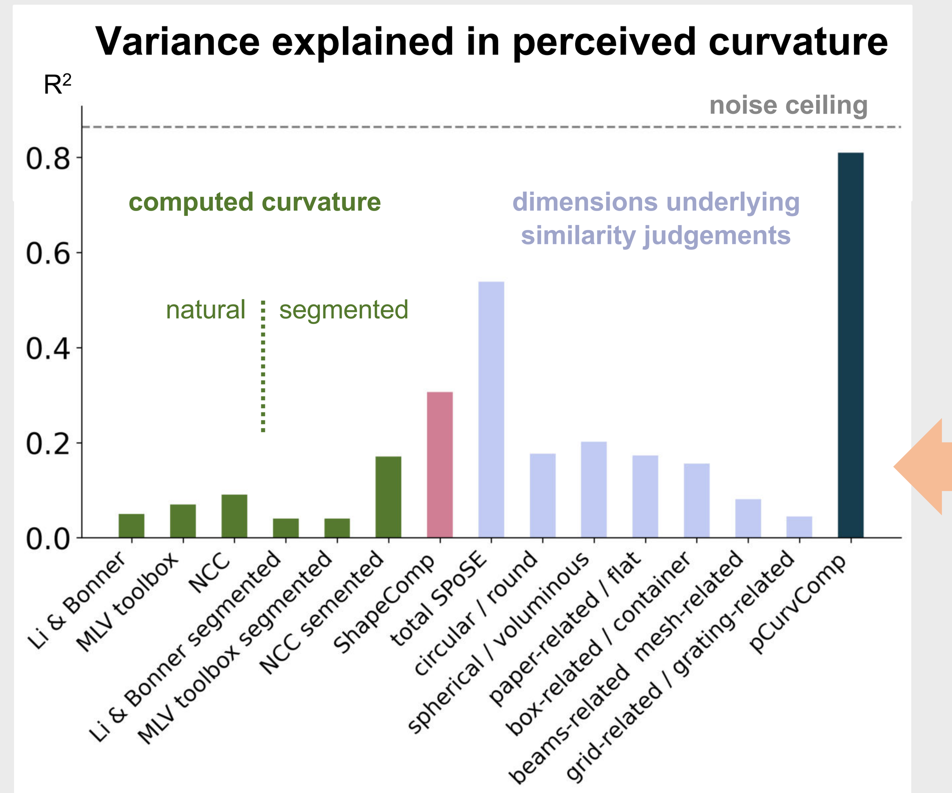
- Curvature is suggested as a fundamental organizational dimension of object responses [1, 2]
- While there may be a clear definition of curvature for artificial stimuli [3], defining curvature of naturalistic object images remains challenging

How can we quantify perceived curvature of natural images, and how does this perceived curvature relate to patterns of brain activity?

How does perceived curvature relate to other curvature, texture and shape measures?

- Low correlation of curvature measures
- Perceived curvature is best explained by shape-related measures

	curvature	MLV	Li & Bonner	NCC	MLV seg.	Li & Bonner seg.	NCC seg.
curvature	1.00						
MLV	0.26	1.00					
Li & Bonner	0.22	0.14	1.00				
NCC	0.30	0.46	0.11	1.00			
MLV seg.	0.20	0.72	0.10	0.28	1.00		
Li & Bonner seg.	0.20	0.11	0.57	0.09	0.10	1.00	
NCC seg.	0.41	0.39	0.11	-0.01	0.47	0.09	1.00



How can we automatically quantify the perceived curvature of novel images?

- Ensemble model (CLIP, Resnet50, & ConvNext [10-12]) predicting perceived curvature of natural images
- Performance closely approaches noise-ceiling

pCurvComp
$R^2 = 0.81$

Validation with external dataset (Long et al. 2018)

$R^2 = 0.70$ $R^2 = 0.19$

METHODS

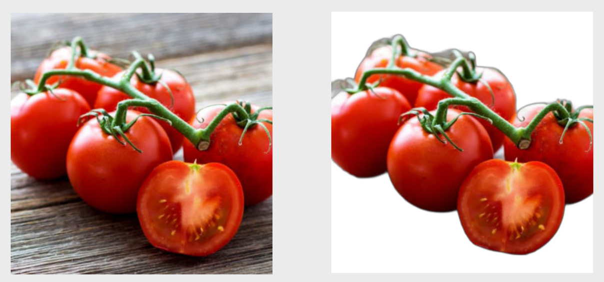
Perceived curvature ratings

- Rich dataset of curvature ratings for > 27k natural object images of the THINGS database [4, 5]

Split-half reliability
r = 0.93

Computed curvature

- MLV toolbox [6]
- Li & Bonner [1]
- Normalized contour curvature (NCC) [3]



ShapeComp [7]

- image-computed shape descriptors reflecting shape similarity ratings

SPoSE Dimensions [8]

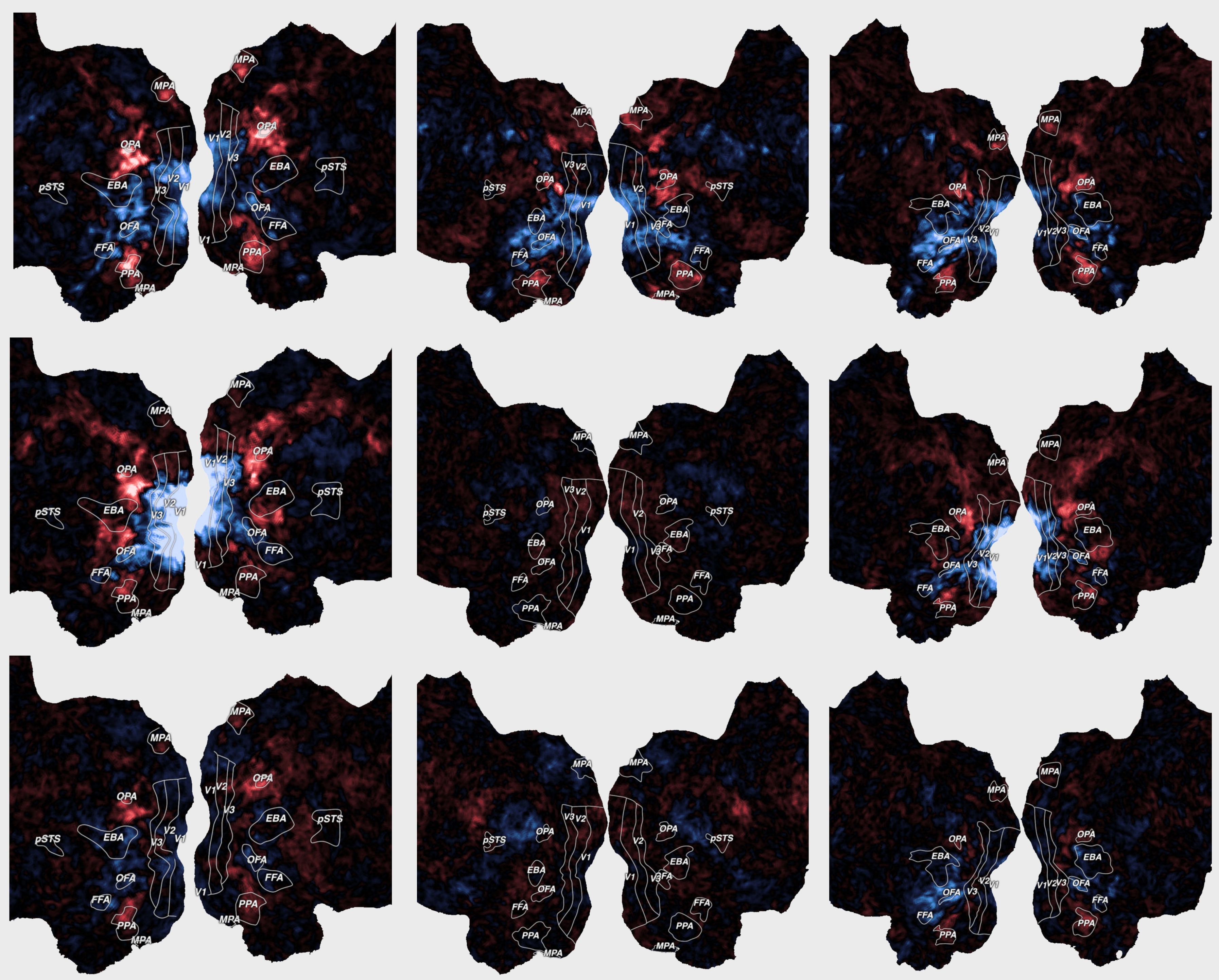
- Shape and texture related dimensions based on human similarity judgements of object images

THINGS-fMRI [9]

- fMRI responses of 3 participants to 8640 natural images of 720 object concepts

How do the curvature measures relate to neural object responses?

- Perceived curvature best predicts responses in higher-level visual cortex, with rectilinear preferences in scene-selective regions and interleaved curvy preferences



CONCLUSION

- Discrepancies between curvature measures highlight the **challenges of quantifying curvature** of natural object images
- Humans can **reliably judge** object curvature, which differs from computed curvature
- This perceived curvature is a candidate **organizational dimension** of responses to natural object images
- Recognizing its importance, we make perceived curvature image-computable with **pCurvComp**

Future directions:
Identify the image-features pCurvComp relies on for its predictions

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