# TASK-DEPENDENT CONTRIBUTION OF HIGHER-ORDER STATISTICS TO NATURAL TEXTURE PROCESSING


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## BACKGROUND

**Prior work:** Portilla-Simoncelli statistics successfully capture aspects of texture perception[1] **(Figure 1A)**, peripheral vision perception[2,3], and physiology of mid-level visual areas[4-7]. However, the higher-order statistics (HOS) of the model are a weak segmentation cue for humans in peripheral vision, in contrast to the simpler spectral statistics[8] (**Figure 1B**).

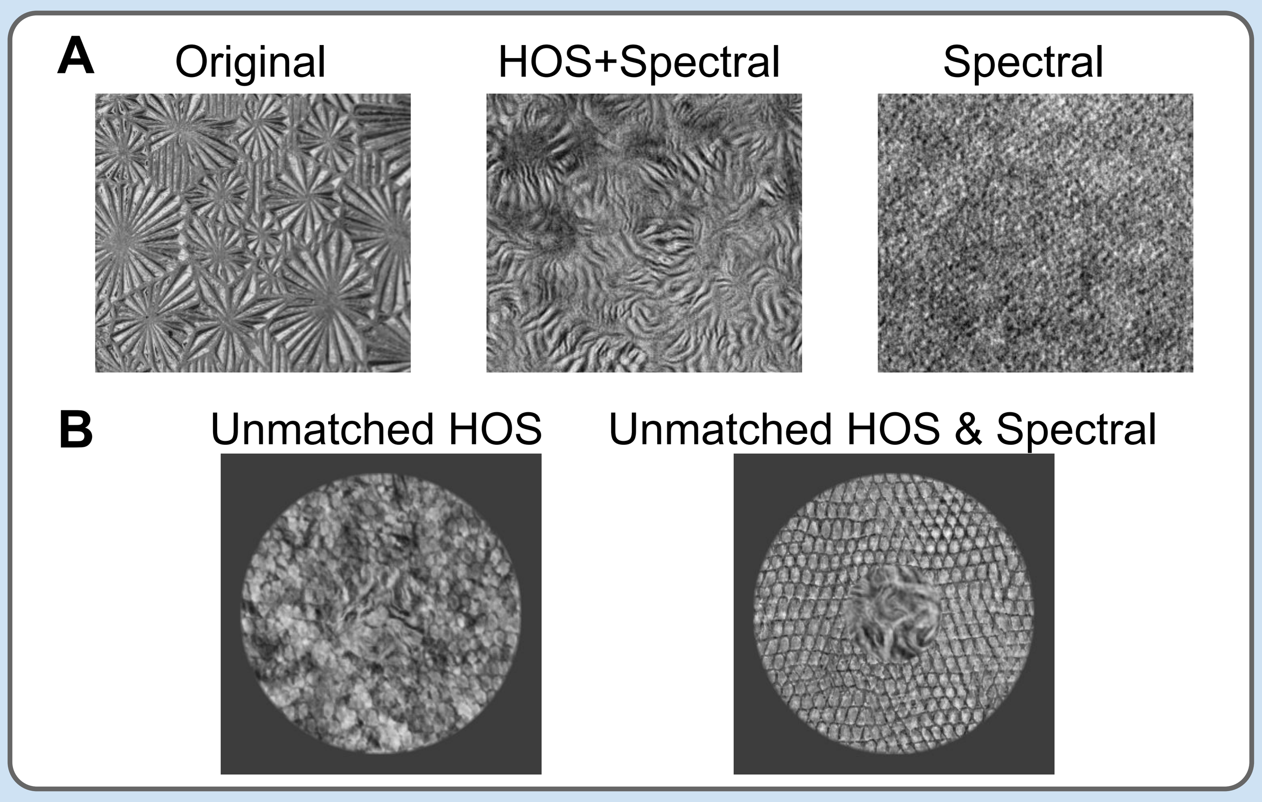


**Figure 1. HOS are essential for texture perception but not segmentation. A)** Texture synthesis. Left: Original, Middle: Portilla-Simoncelli synthesis (HOS+Spectral), Right: Phase scrambling. **B)** Texture segmentation[8]. Left: HOS difference, Right: HOS+Spectral difference

In previous modeling work[9], we showed that HOS and spectral statistics are redundant for a natural image segmentation task, which may explain the minor role of HOS for segmentation in humans[8].

**Hypothesis:** HOS are important for texture perception and physiology because they are important to support texture classification. The task dependent use of HOS by humans reflects the task-dependent contribution of these features to natural image processing.

## METHODS

**Datasets:** 11 public datasets that we divide into 4 types of classification (**Figure 2**): 1) Instance, 2) Material, 3) Perceptual, 4) Scene.

**Classification:** We trained linear classifiers on the different texture statistics of the images, and compared the cross-validated performance of the classifiers. We normalized each set of statistics, performed PCA, and used the components that retain 95% of the variance.

**Segmentation:** We computed texture statistics of adjacent patches in natural images (Berkeley Segmentation Dataset), and took the absolute difference between their statistics. We trained classifiers to predict if a pair of patches belongs to the same or to different image segments using these differences in statistics.

**Log-odds ratio (LOR):** We used the LOR between classifiers as a measure of the advantage of HOS over spectral statistics.
LOR~0 ➡ the two classifiers perform similarly
LOR>0 ➡ HOS > spectral statistics

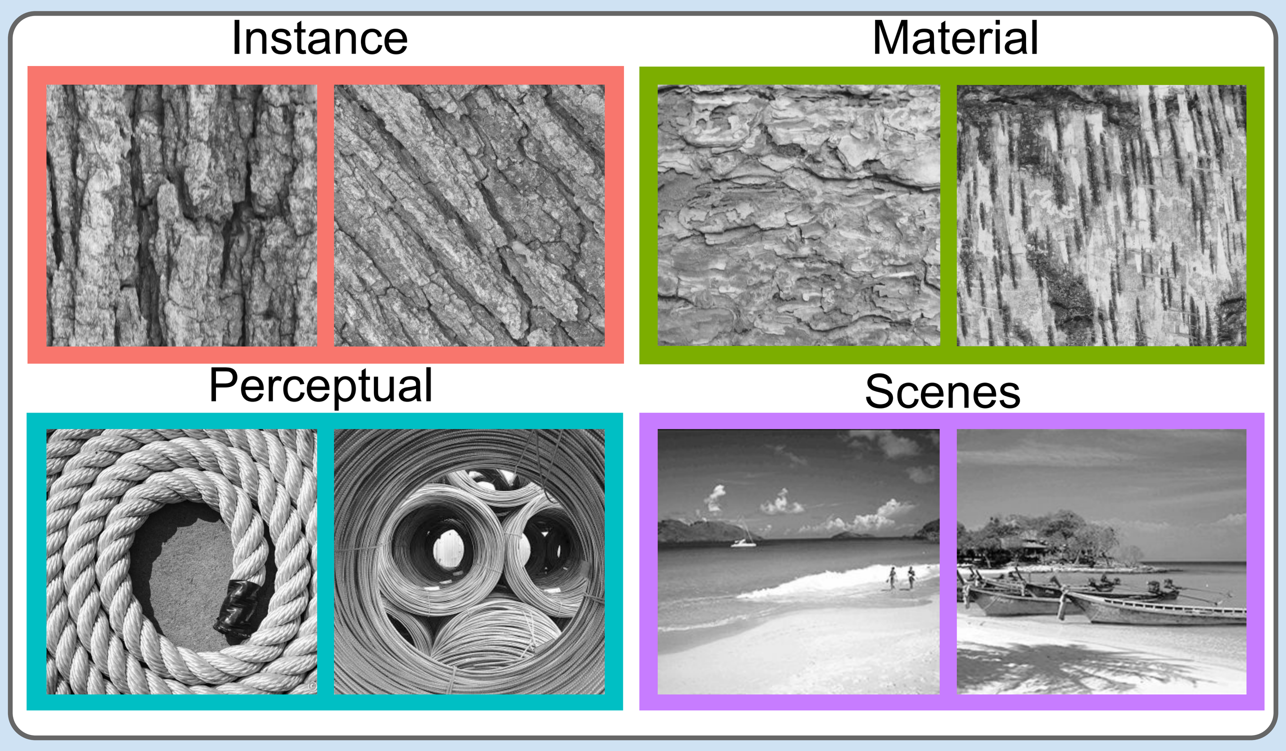


**Figure 2. Types of classification tasks.** Pairs of samples from a random class of each kind of dataset.

## RESULTS

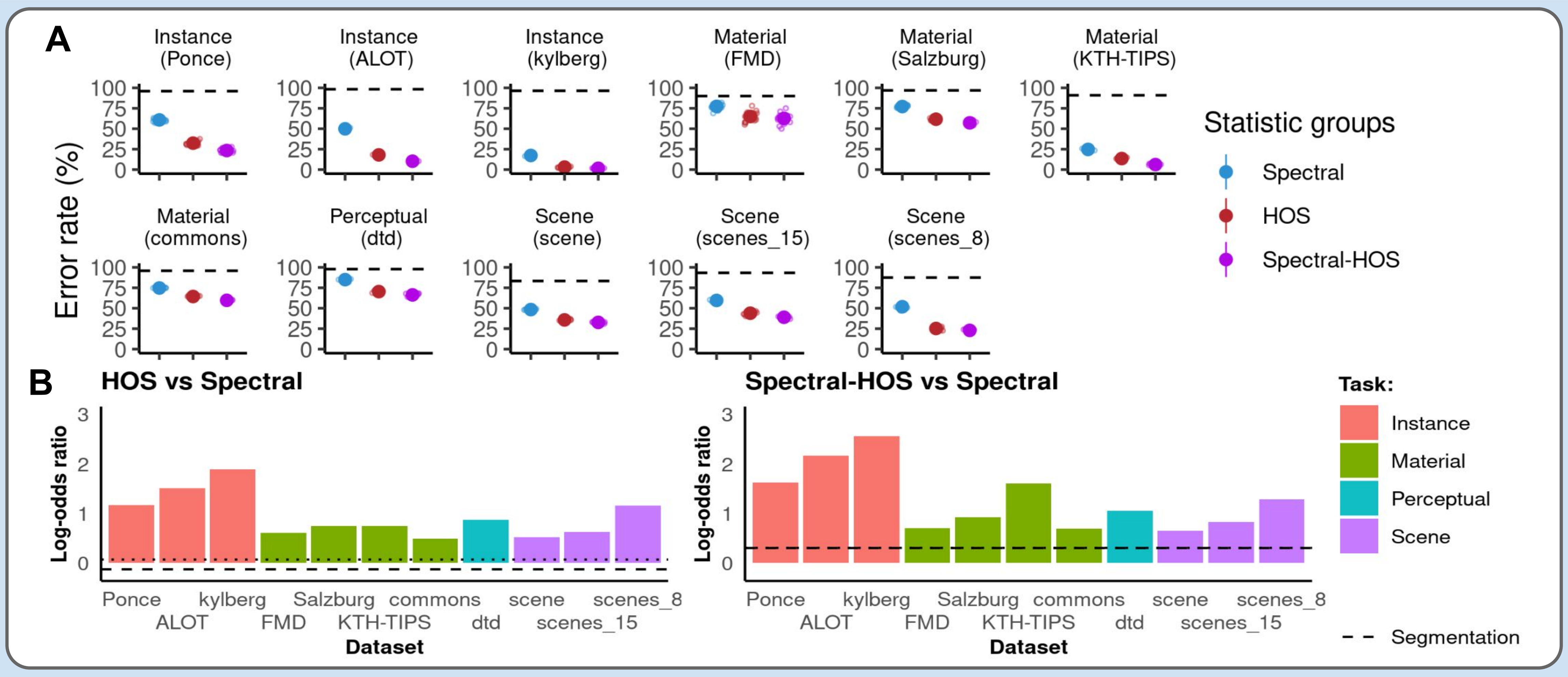


**Figure 3. HOS outperform spectral statistics for classification, unlike segmentation. A)** Classification error for each dataset and each statistics set. Dashed lines indicate chance performance. **B)** LOR between HOS classifiers and spectral statistics classifiers. Dashed lines show the LOR for the segmentation task.

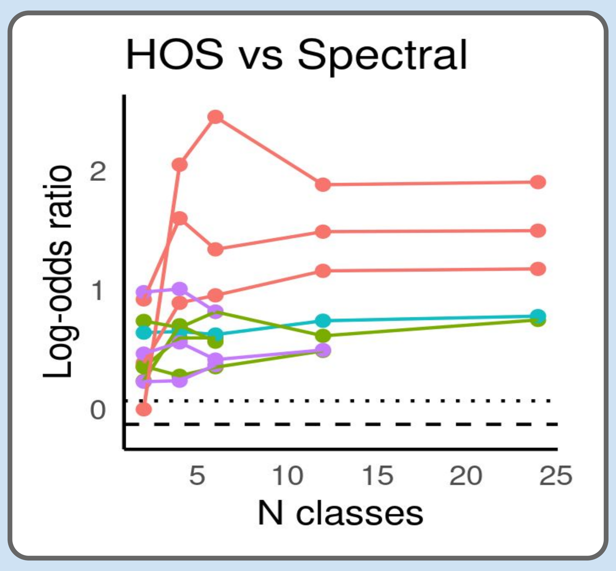


**Figure 4. Differences in LOR are not due to the number of classes in each dataset.** We subsampled the number of classes of each dataset, to test the effect of the number of classes on the advantage of HOS over spectral statistics. Even when using only 2 classes, the HOS are more useful for classification (LOR>0) than for segmentation (LOR~0). Also, the differences between classification tasks persist when matched in the number of classes. Color code and dashed lines as in **Figure 3B**.

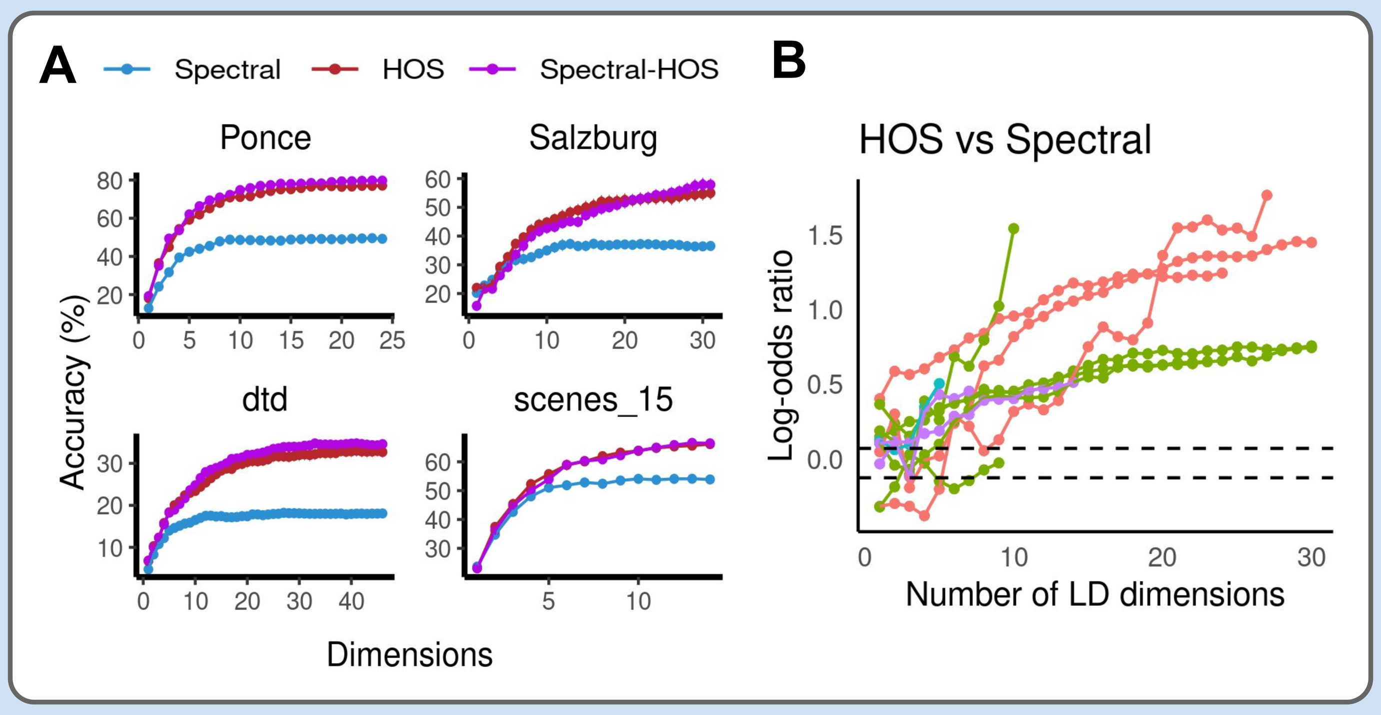


**Figure 5. HOS outperform spectral statistics at higher dimensions, but not at low dimensions.** We matched the different statistics for number of dimensions using Linear Discriminant Analysis, and tested their accuracy. **A)** Performance for different numbers of dimensions, **B)** LOR for different numbers of dimensions. HOS advantage over spectral statistics grows with the number of dimensions.

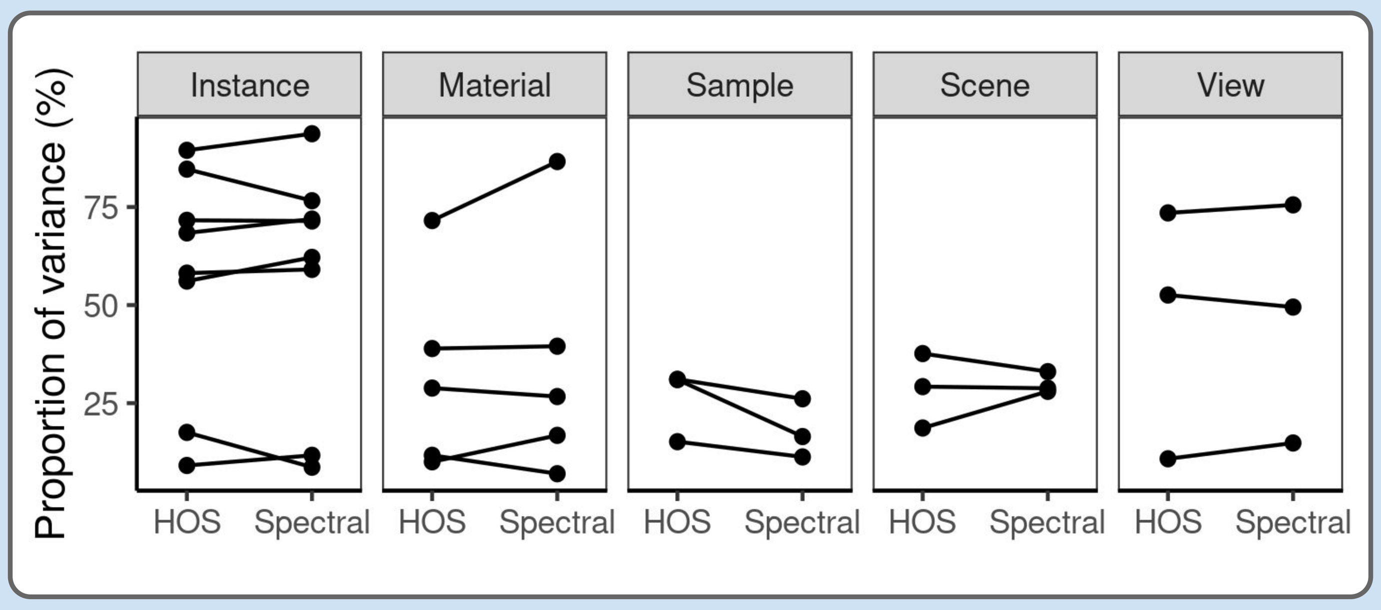


**Figure 6. HOS and Spectral statistics are equally susceptible to variability sources.** We decompose the variance of the different sets of statistics into the contributions of different variability sources. Panels indicate source of variability, and points joined by lines correspond to the variability of spectral statistics and HOS for a same dataset.

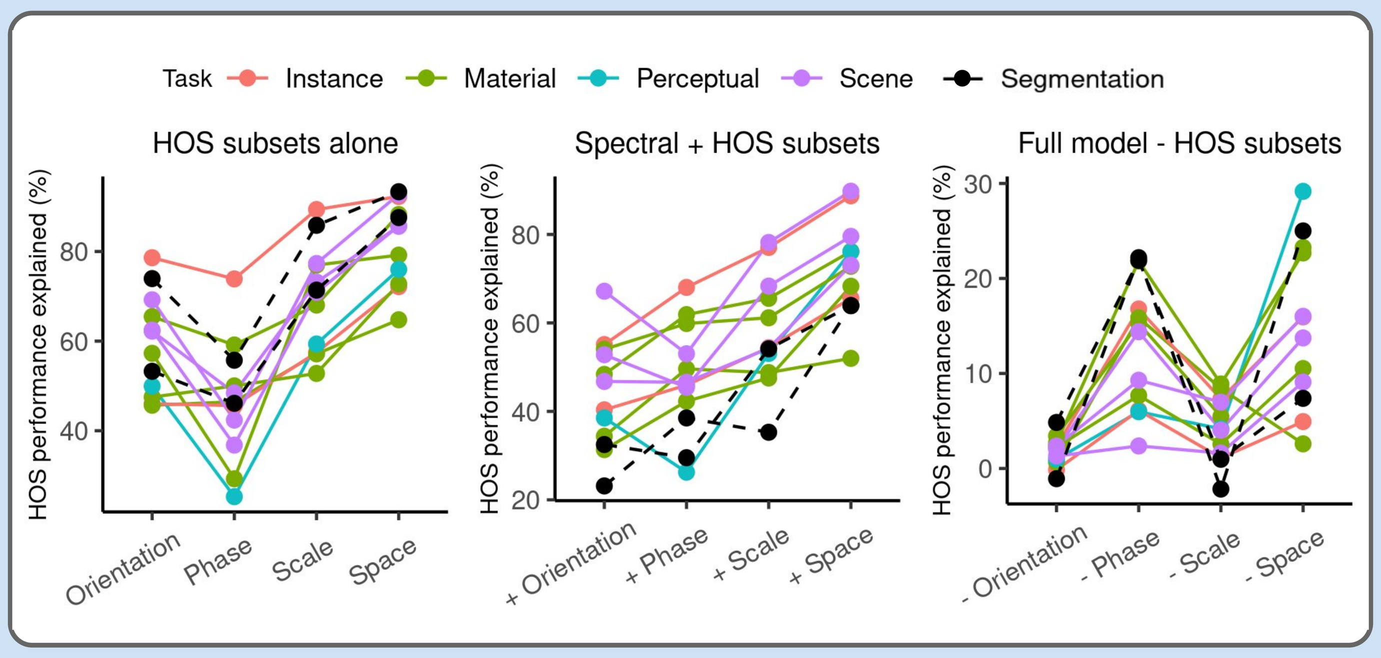


**Figure 7. Subsets of HOS contribute similarly to classification subtasks and to segmentation.** We analyzed the relevance of the different subsets of HOS. We added (or removed) the subsets individually to a baseline model, and compared the change in performance to the change of adding (or removing) the full set of HOS. We show what percentage of total HOS performance is achieved by each HOS subset.

## CONCLUSIONS

- HOS strongly outperform spectral statistics for classification but not for segmentation, which may explain their task-dependent use by humans
- The difference between HOS and spectral statistics varies between classification sub-tasks
- The advantage of HOS over spectral statistics for classification is due to a larger number of informative dimensions, and not due to differences in variability or invariance
- The contribution of different HOS subsets is consistent across datasets and tasks
- These results outline the importance of task-specific analyses of natural image statistics


**References: 1.** Portilla, J.; Simoncelli, E.P. (2000) *IJCV* 40; **2.** Balas, B.; Nakano, L.; Rosenholtz, R. (2009) *JOV* 9(12); **3.** Freeman, J.; Simoncelli, E.P. (2012) *Nat Neurosci* 14(9); **4.** Freeman, J. et. al. (2013) *Nat Neurosci* 16(7); **5.** Ziemba, C.M. et. al. (2016) *PNAS* 113(22), **6.** Okazawa, G.; Tajima, S.; Komatsu, H. (2015) *PNAS* 112(4). **7.** Okazawa, G.; Tajima, S.; Komatsu, H. (2017) *Cereb. Cortex* 27(10)) **8. Herrera-Esposito, D.; Coen-Cagli, R*; Gomez-Sena, L.* (2021) *JOV* 21(1). 9 Herrera-Esposito, D.; Gomez-Sena, L; Coen-Cagli, R. (2021) *Vis Res* 187.**