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Shape recognition: convexities, concavities and things in between

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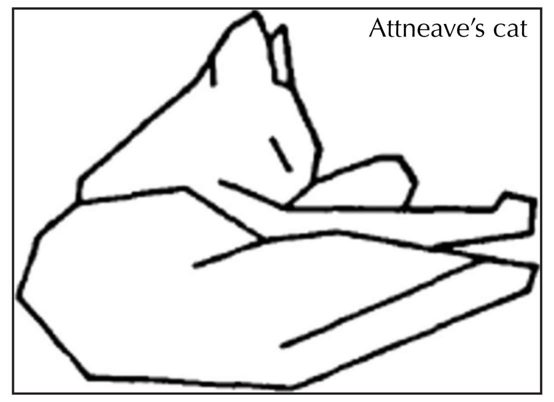
1. INTRODUCTION

- Points of maximum curvature have been suggested to contain crucial information about shape (Attneave, 1954; Biederman, 1987)



- Previous studies on object recognition have drawn different conclusions regarding the importance of specific object features, such as convexities, concavities and intermediate points
- Some studies found evidence for a predominant role of convexities, whereas others favored concavities or intermediate parts

Convexities: Bertamini, 2001; Bertamini, Helmy, & Hulleman, 2013; fMRI (LOC) Haushofer et al., 2008)
Concavities: Barenholtz et al., 2003
Both: Attneave, 1954; Bertamini, 2008; Bertamini & Farrant, 2005; Biederman, 1987; Pasupathy & Connor, 2002; Carlson et al., 2011

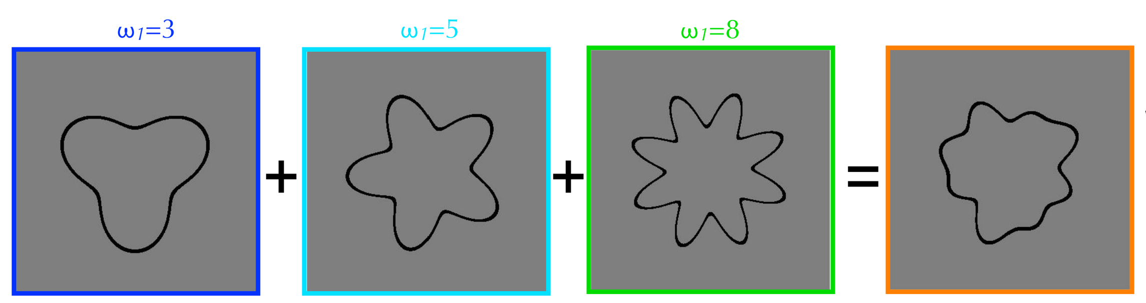
- Previous neurophysiological studies desrcibed neurons in V4 which are selectively responsive to contour features, such as convexities and concavities at specific locations within their receptive fields (e.g. Pasupathy & Connor, 2002)
- Carlson et al. (2011) suggeseted a sparse object coding scheme in midlevel visual cortex based on regions of acute convex and concave contour curvature
- However, most of studies have employed familiar objects or simple geometric shapes not necessarily containing curves (polygons) as their stimuli
- We used a novel set of shapes with well-defined convexities, concavities and points between convexities and concaves

2. AIMS

The aims were:
1) To measure shape recognition for unfamiliar random shapes
2) To compare the contribution of convexities, concavities and inermediate parts of the shape
3) To test various Models that predict the observed patterns of results

3. METHODS

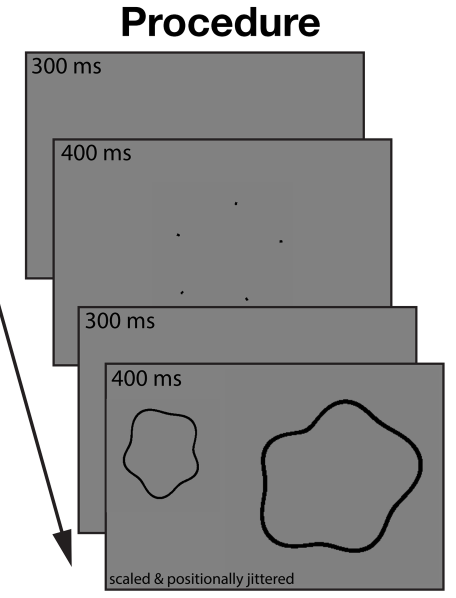
The shapes were composed of the sum of three different radial frequency (RF) components with random phases segmented to remove all but variable lengths of contour centred on the feature of interest



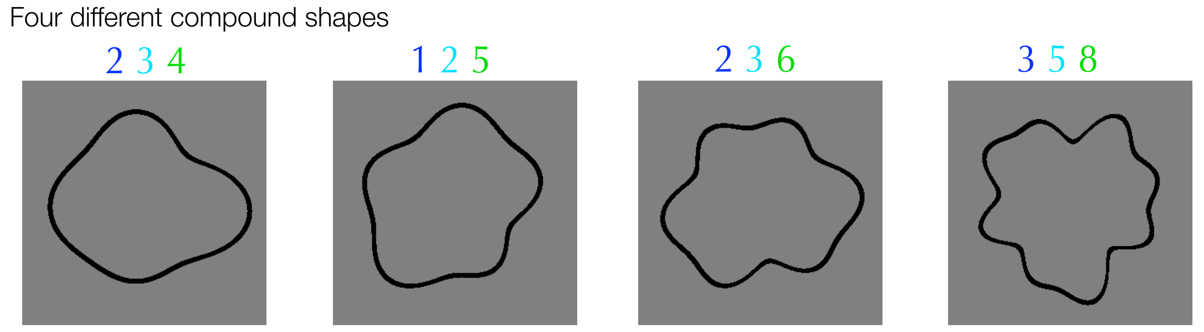
$$RF_{compound}=r_{mean}(1+A_1\sin(\omega_1\theta+\varphi_1)+A_2\sin(\omega_2\theta+\varphi_2)+A_3\sin(\omega_3\theta+\varphi_3))$$

- r_{mean}: mean radius of underlying circle (=100 Pixel)
- A: modulation amplitude (=0.1)
- ω_1: radial frequency
- θ: polar angle
- φ_1: phase / orientation (random)

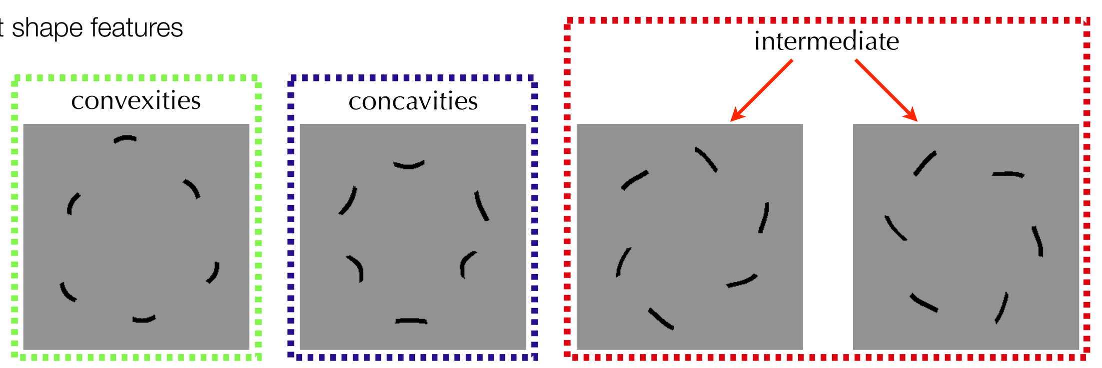
Procedure



Four different compound shapes



- different shape features

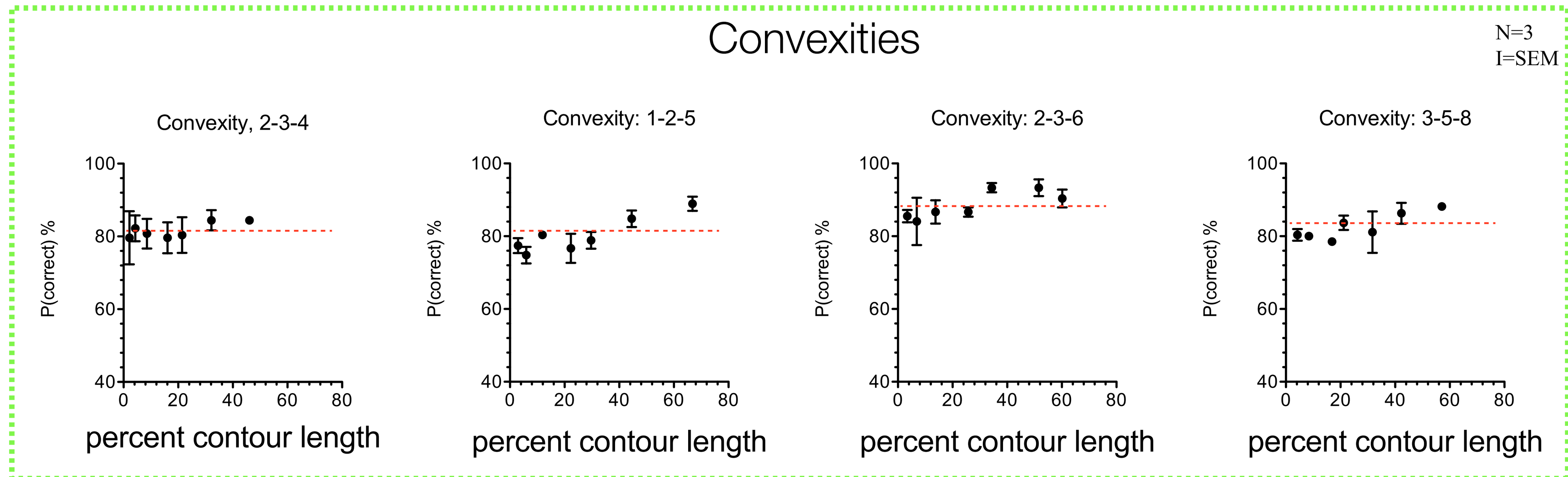


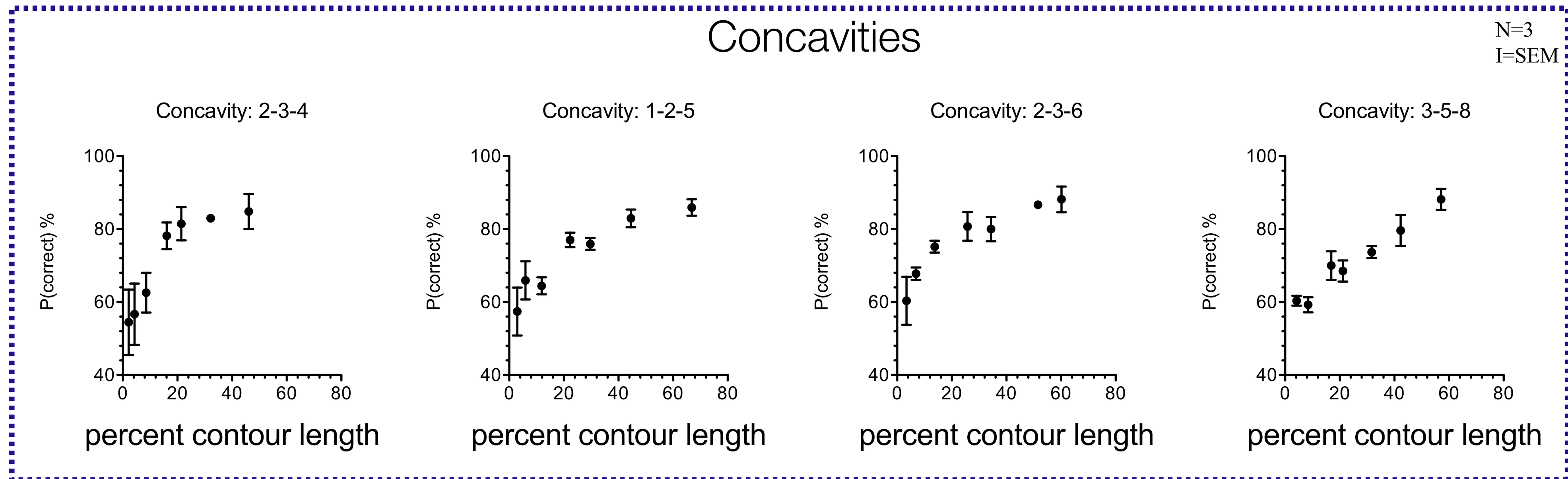
- The task was to match one of two closed shapes to the test stimllus showing different arc length around points of:
  1) convexities
  2) concavities
  3) intermediate parts

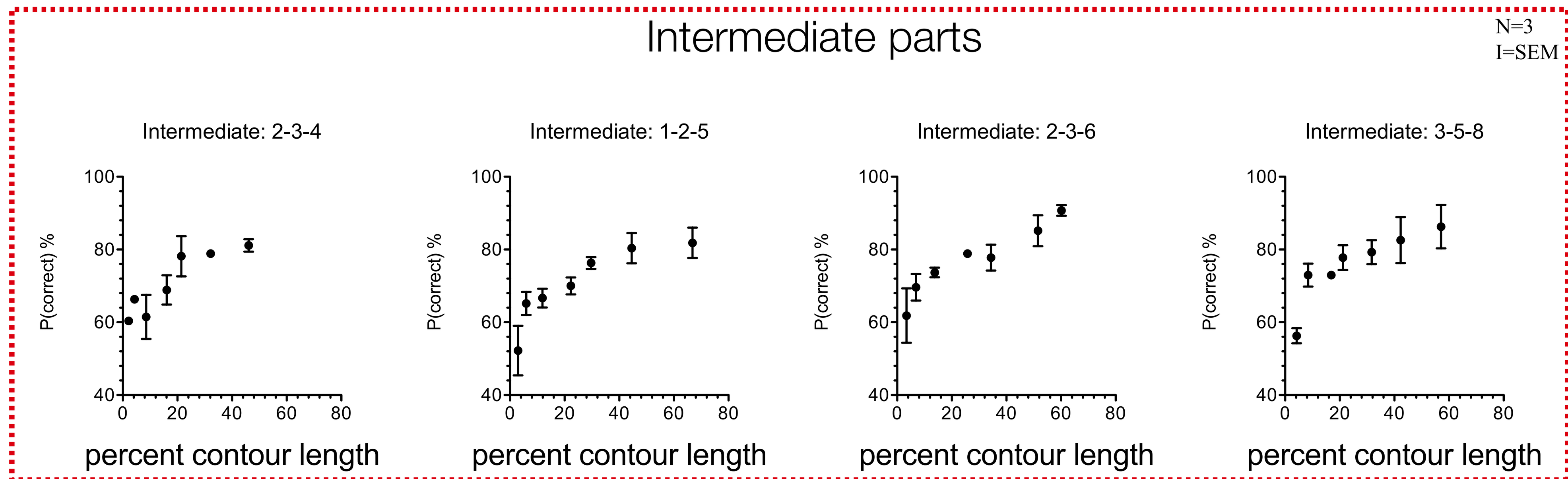
Signal Shape:
- The phase (φ) of the RF components was always randomly varied, so that the observer were never presented with the same shape twice within a trial

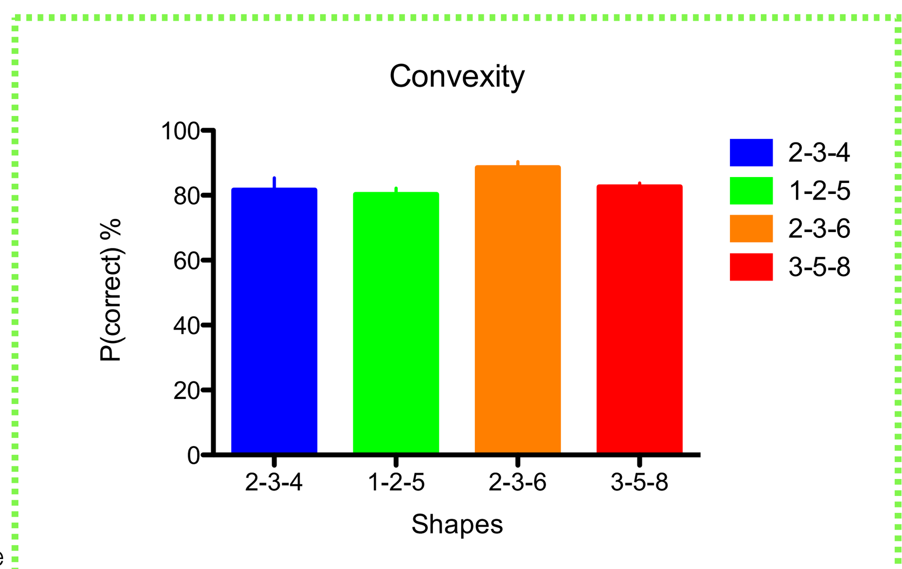
Noise Shape:
- The noise shape was composed of the same RF components as the signal shape, but with random phase (φ)

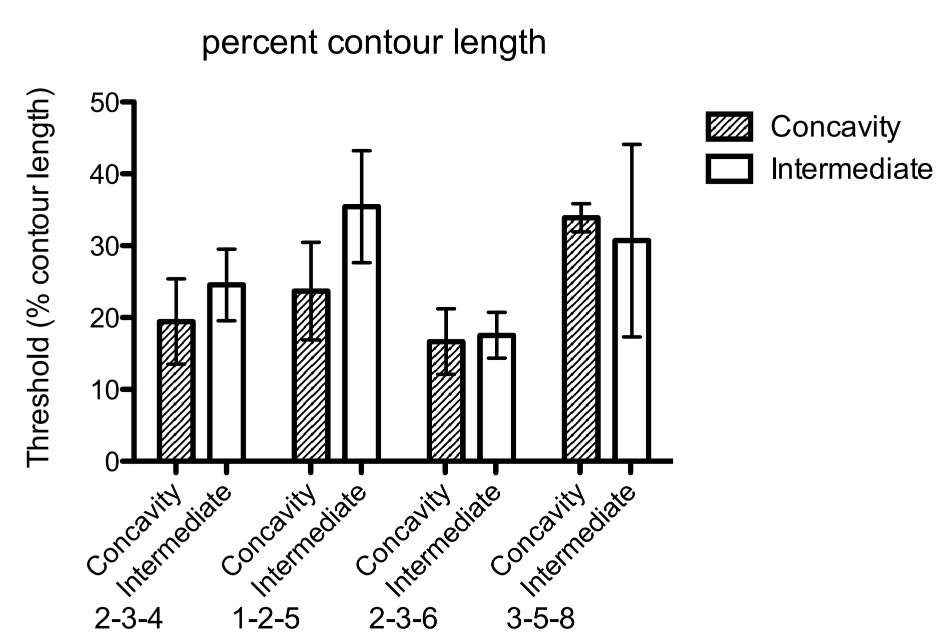
3. RESULTS











4. DISCUSSION

- Results show that for very short (dot-sized) segments lengths, performance was significantly higher for convexities than for either concavities or intermediate points.
- Performance for convexities remained constant as a function of segment length, and...
  ...although performance improved with segment length for concavities and intermediate points,it only reached convexity performance at the largest lengths tested.
- This suggests that the longer segment lengths for concavities and intermediates enable an easier interpolation of points of convex curvature maxima, which might be used to recognize the shape.
- No significant differences between concavities and intermediate points were found.
- No significant differences between the different shapes.
- Performance is scale-invariant.
- Results suggest that for this class of closed shapes, shape is encoded from the positions of convexities, rather than from positions of either concavities or intermediates.

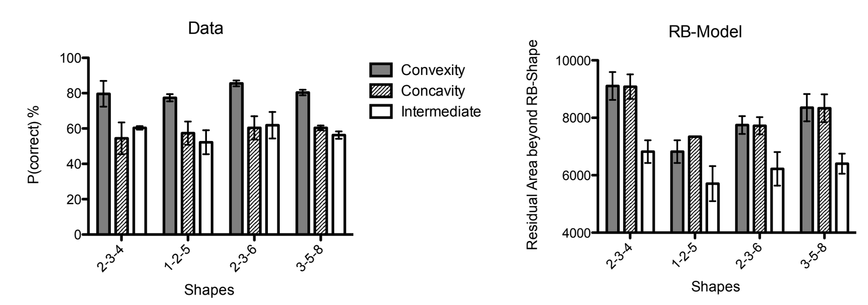
5. Rubber Band Model

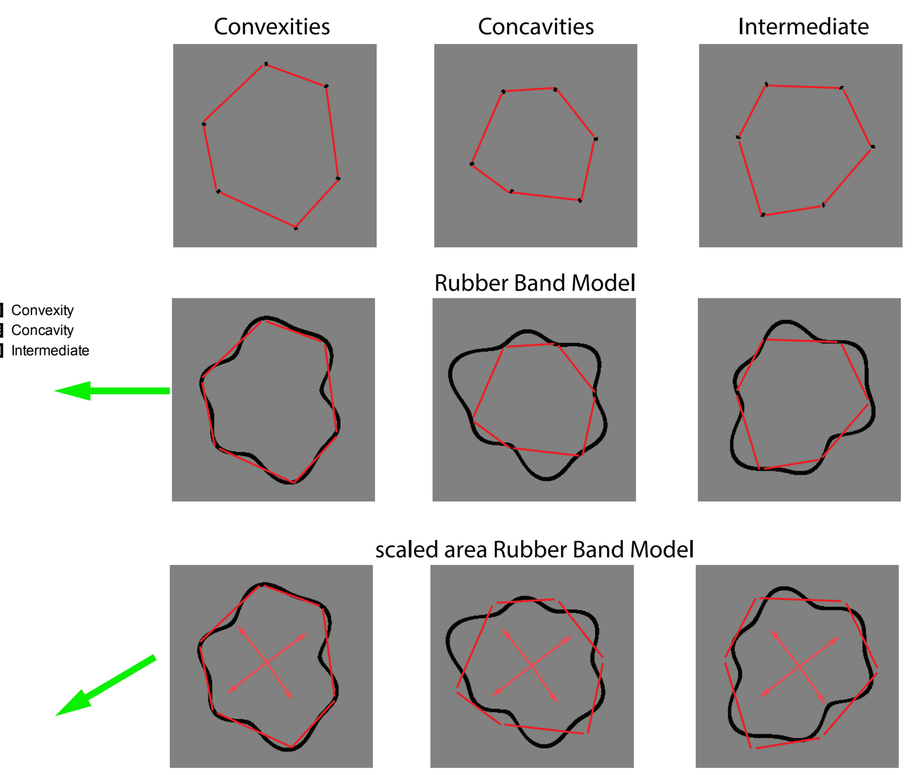
The Model assumes that the shape is encoded by extracting the location of either convexities, concavities or interemdiate points and combines these points by staight lines to form a coarse polygonal Model Shape (i.e. putting a rubber band around these points / red shapes in Figure).
The hypothesis is that the resulting Model Shape captures/desribes the presented smooth Test Shape more acurately when convexities are presented and predicts poorer, but similar descriptions for concavites and interemdiate features.
Each Model prediction was calcualted for 1000 shapes (Mean,±STDEV)

Model I

Model description:
- to calculate the residual area between the Model Shape and the Test Shape

Hypothesis:
- the residual area between the Model Shape and Test Shape is smaller for convexities than for concavities and intermediate points



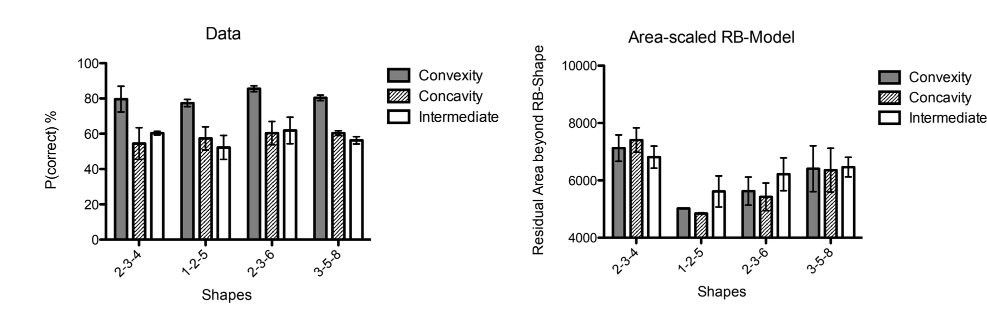


Results:
- the Model predicts the best performance for intermediate
- the model does not capture the observed data

Model II

Modification to Model I: Signal and noise shapes were randomly scaled in the experiment. In order to encorporate this scaling into the model, the area of the Model Shape (red) was equalized with the Test Shape.
Model description:
- to calculate the residual area between the Model Shape and the test shape

Hypothesis:
- the residual area between the scaled Model Shape and Test shape is smaller for convexities than for concavities and intermediate points



- the Model predicts a similar performance for all shape features
- the model does not capture the observed data

6. Conclusion

Shapes are encoded from the positions of convexities, rather than from positions of either concavities or intermediates.

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