

A Meta-Theory of Boundary Detection Benchmarks



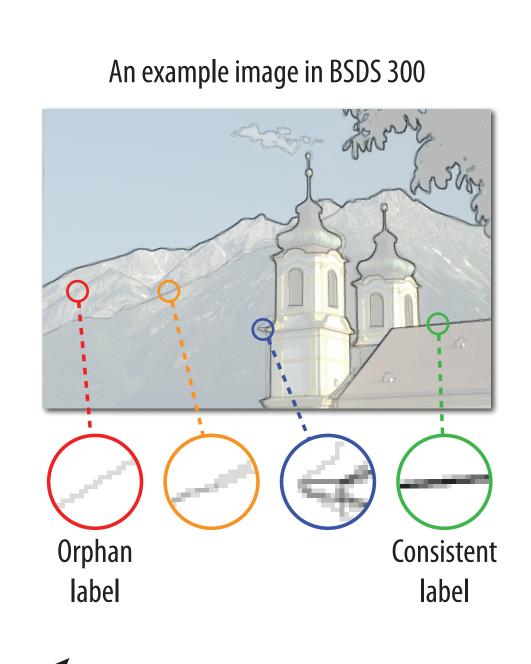
Xiaodi Hou Computation and Neural Systems, Caltech

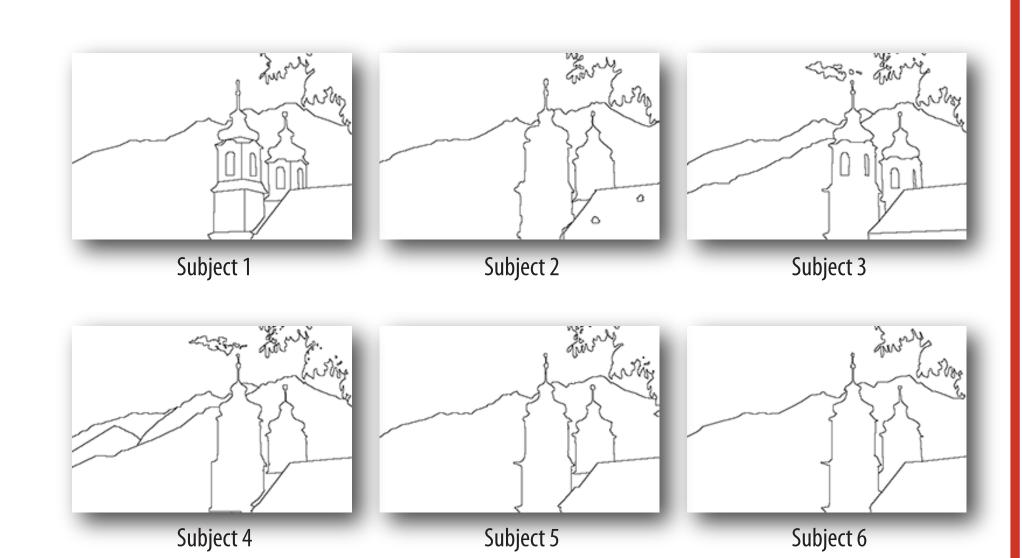
Alan Yuille Department of Statistics, UCLA

Christof Koch Computation and Neural Systems, Caltech

Benchmarks of boundary detection

Human boundary labels are not always consistent

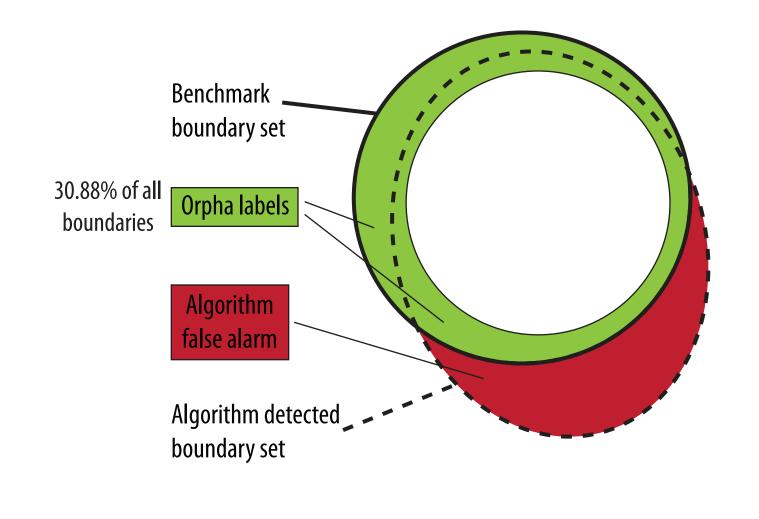


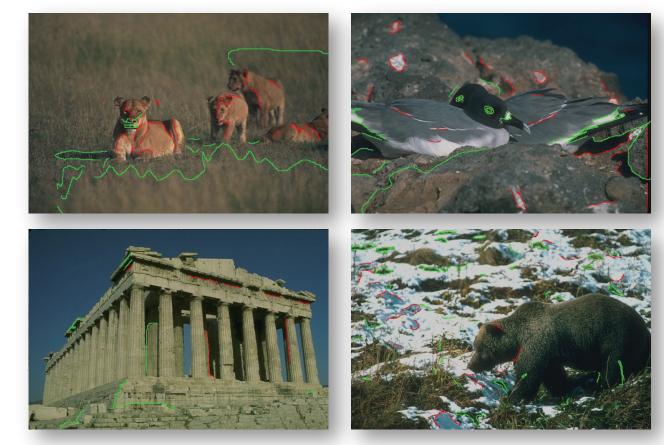


Decreasing label consistency

Evaluating the risks of a benchmark

Algorithm false alarms v.s. human orphan labels

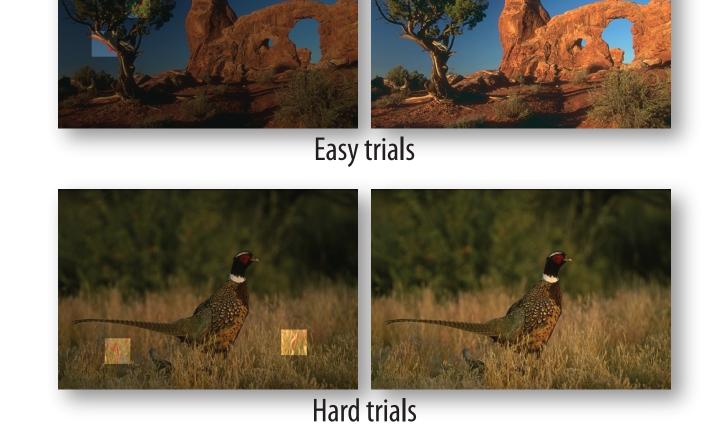




Red lines: algorithm false alarms. Green lines: human orphan labels

Two-way force choice experiment

Choose the stronger boundary segment from the two candidates



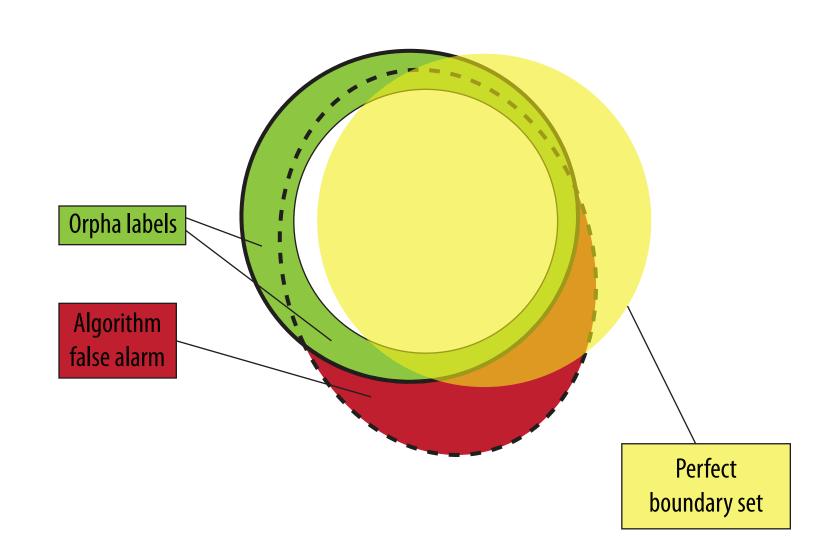
Experimental result of 5 subjects and 100 images: Algorithm false alarms

beats human orphan labels

in 44% trials!!

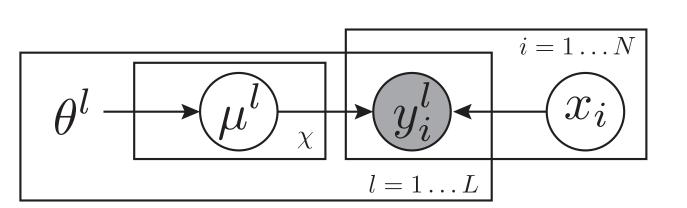
The risk of a boundary detection dataset

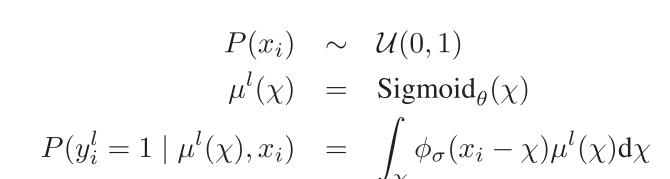
 $R(\mathcal{S}, \mathcal{A}) = P(x_i < x_j \mid s_i \in \mathcal{S}, s_j \in \mathcal{A} \setminus \mathcal{S})$



- Boundary segment i
- Perceptual strength of boundary segment i
 - Imperfect human-labeled boundary set
- Algorithm (pB) detected boundary set
- \mathcal{S}_{τ} Risk-free perfect erfect boundary set

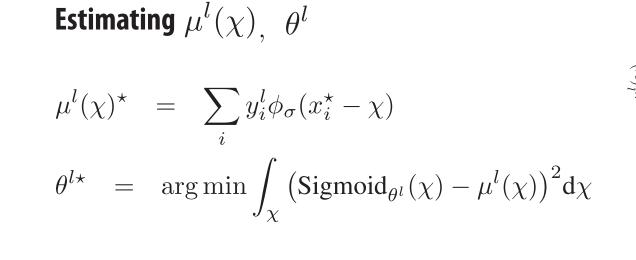
The Graphical Model of Labeling

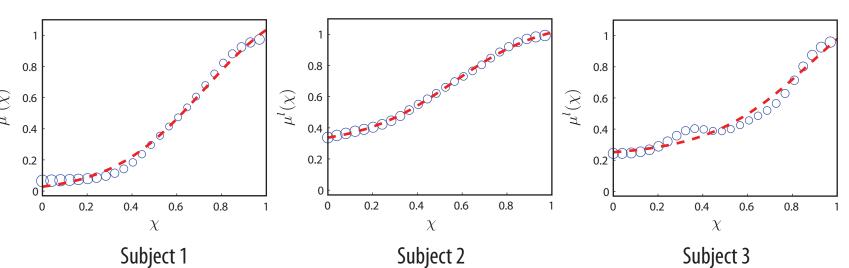


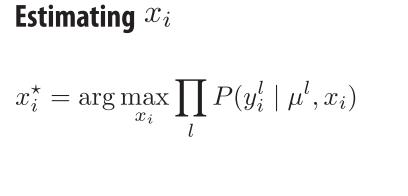


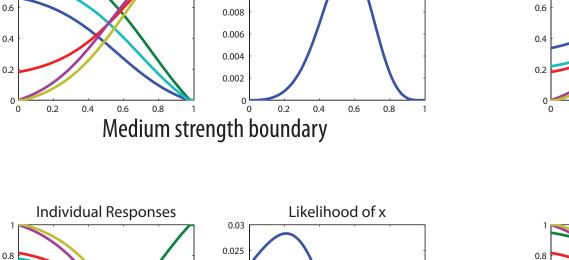
Subject I's response to boundary segment i (observed) x_i Perceptual strength of boundary segment i (hidden)

Perceptual strength of boundary segment i (hidden) Perceptual strength of boundary segment i (hidden)

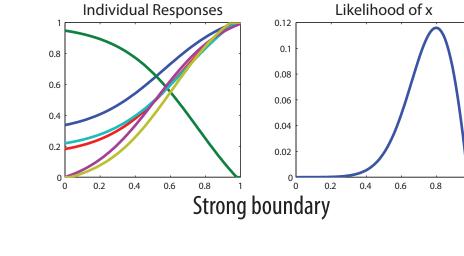




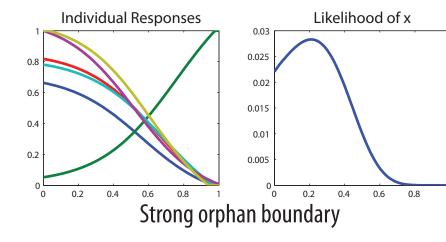


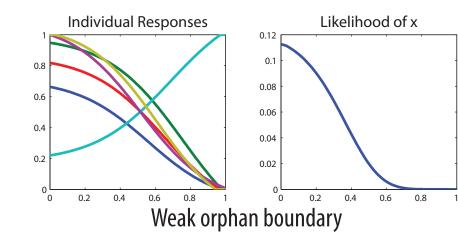


Likelihood of x



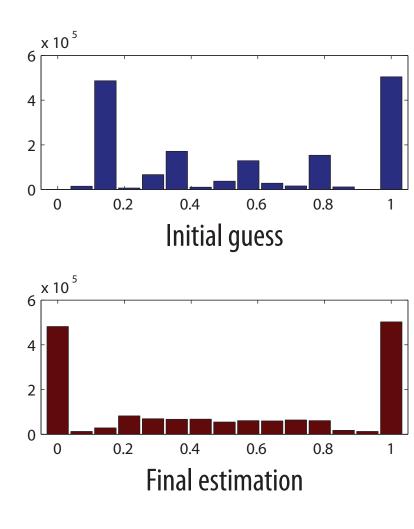
Some orphan labels annotated by (unnecessarily) detailed labelers can be filtered out by the majority of more determined labelers.





Experiment Results

Distributions of perceptual strength Initial guess



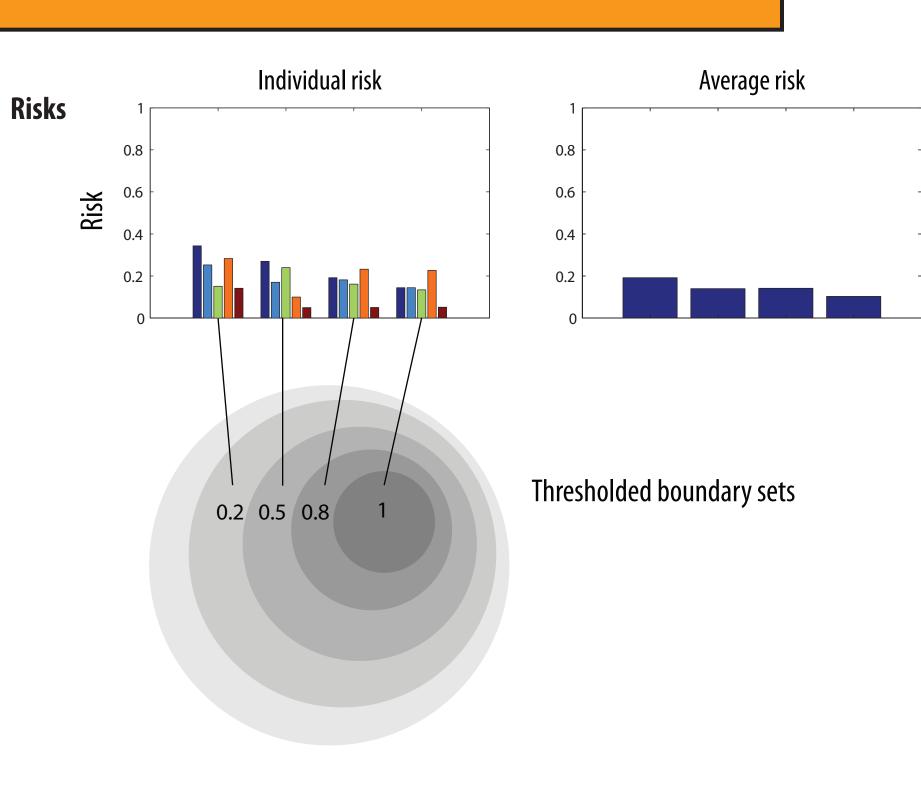


Image results

