# Multi-cue mid-level grouping

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### Overview



#### MOTIVATION

- region proposals [CPMC, Selective Search] are far fewer than sliding windows
- yet, thousands of regions still contain a great deal of noise
- can we exploit mid-level grouping cues to improve precision?

#### CONTRIBUTIONS

- we directly tackle the front-end generation of regions
- we use mid-level cues to eliminate false positive regions
- we learn the best combination of grouping cues

# Grouping cues: non-accidental regularities

ENERGY FUNCTION

APPEARANCE CUE

# Inference and learning

HIDDEN SCALE

- assign costs to binary superpixel labelings
- energy potentials express grouping cues

$$E(\mathbf{y}; \mathbf{x}) = \sum_{cue} \mathbf{w}_{cue}^{\mathsf{T}} \sum_{C} \phi_{cue}(\mathbf{y}_{C}; \mathbf{x})$$

 $CLOSURE \ CUE \ [Levinshtein \ et \ al., \ ECCV'10]$ 

- discourage regions with gaps along boundary
- minimize  $Gap(\mathbf{y}; \mathbf{x}) = \sum_{x \in \partial(\mathbf{y})} g(x)$ , rewritten as energy potentials





- discourage splitting homogeneous regions
- use similarity in color and texture  $s_{pq}^{col}$ ,  $s_{pq}^{text}$

$$\phi_{\mathsf{app}}(\mathbf{y}; \mathbf{x}) = (s_{pq}^{\mathsf{col}}, s_{pq}^{\mathsf{text}}) \cdot [y_p \neq y_q]$$

#### SYMMETRY CUE [Lee et al., ICCV'13]

- discourage splitting regions in a symmetric part
- each symmetric part encourages cohesion of superpixels inside



take each part's detection score into account

$$\phi_{\text{sym}}(\mathbf{y}; \mathbf{x}) = \max_{s \in S(p,q)} \text{score}(s) \cdot [y_p \neq y_q]$$

- use area potential  $\phi_0(y_p)$  as a prior on scale
- introduce variable  $\lambda$  to adjust  $\phi_0$ 's influence

#### PARAMETRIC ENERGY MINIMIZATION

• minimize  $E^{\lambda}(\mathbf{y})$  for multiple values of  $\lambda$ 

$$\mathsf{E}^{\lambda}(\mathbf{y}) = \mathbf{w}_{1}^{\mathsf{T}} \sum_{p} (\lambda \cdot \phi_{0} + \phi_{1})(y_{p}) + \mathbf{w}_{2}^{\mathsf{T}} \sum_{p,q} \phi_{2}(\mathbf{y}_{pq})$$

parametric maxflow returns a linear number of solutions



#### LEARNING

- solve a standard Structured SVM problem
- fix  $\lambda$  uniformly for loss function

# Results

#### MID-LEVEL CUE TRANSFER

- mid-level grouping cues are shared by all object classes
- cues trained on one object can be applied to other objects
- dataset: Weizmann Segmentations (WSD)

#### CUE COMBINATION

- determine the effect of combining grouping cues
- appearance, closure, and symmetry each contribute to higher





# quality regions

#### REGION PROPOSALS

- compare our method with CPMC and Selective Search
- we improve precision when budget is limited to 100 proposals
- dataset: Weizmann Horses (WHD)

#### CONCLUSIONS

- mid-level regularities are ubiquitous and apply to all object classes
- grouping cues have the greatest impact when combined