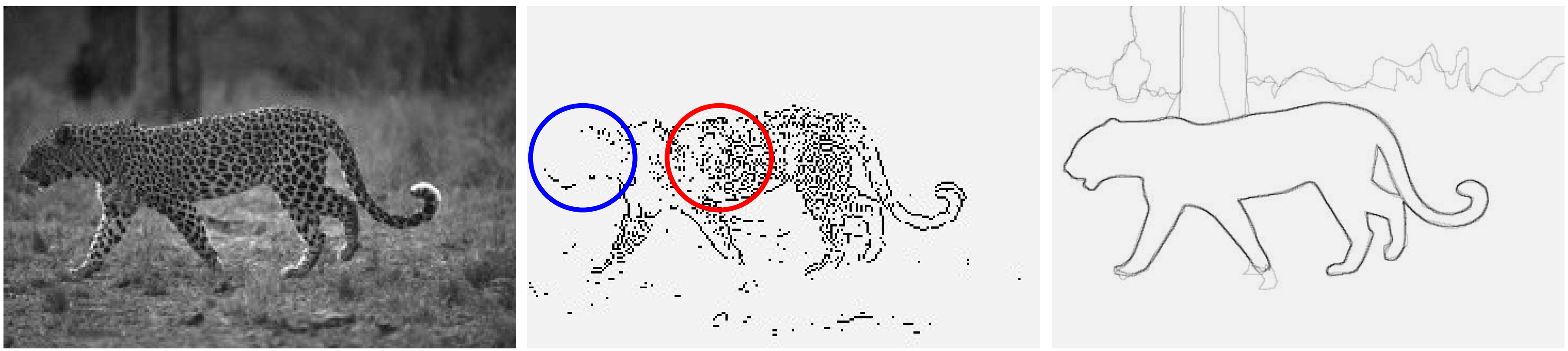
Segmentation Using Multiscale Cues

Stella X. Yu

Computer Science Division, UC Berkeley



segmentation: from edges to boundaries

<u>Multiscale</u> holds the key to overcoming two seemingly irreconcilable difficulties:

false positive: texture
false negative: illusory contours

IEEE CVPR Washington DC 2004: 12 pages

Basic Idea

Traditional approaches:

1. One method for *one* type of phenomena

brightness:	thresholding, morphology, level-set (Leventon, Faugeraus, ...)
curves:	boundary completion (Mumford, Shah, Williams, Jacobs, ...)
texture:	texture segmentation (Tuceryan, Jain, ...)

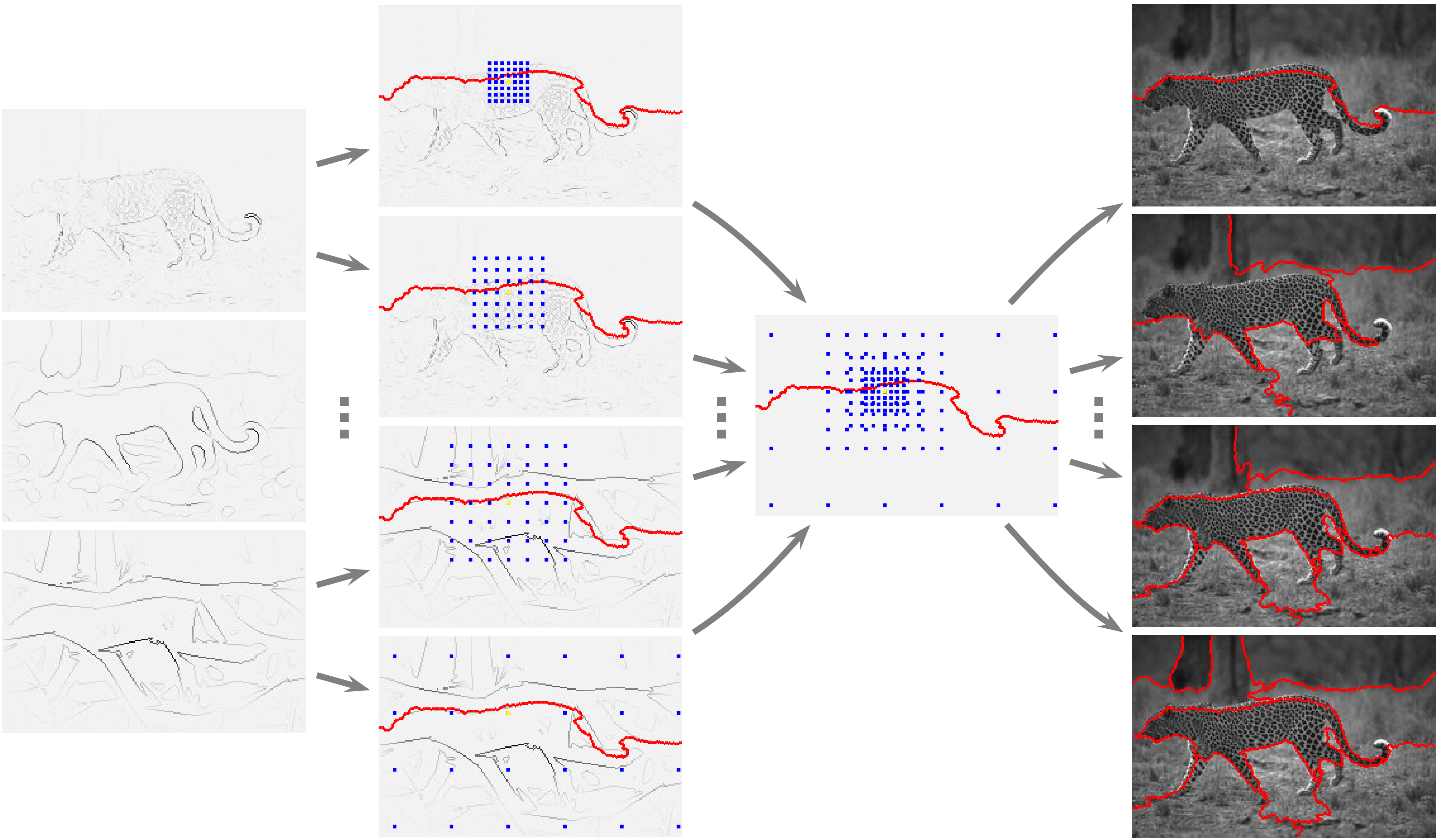
2. One method for *all* types of phenomena: complexity $\uparrow$, flexibility $\downarrow$

more modules:	biologically motivated, facade theory (Grossberg, ...)
more models:	generative, pattern theory (Grenander, Zhu, Mumford, Yullie, ...)
more features:	discriminative, graph cuts (Shi, Malik, Leung, Belongie, ...)

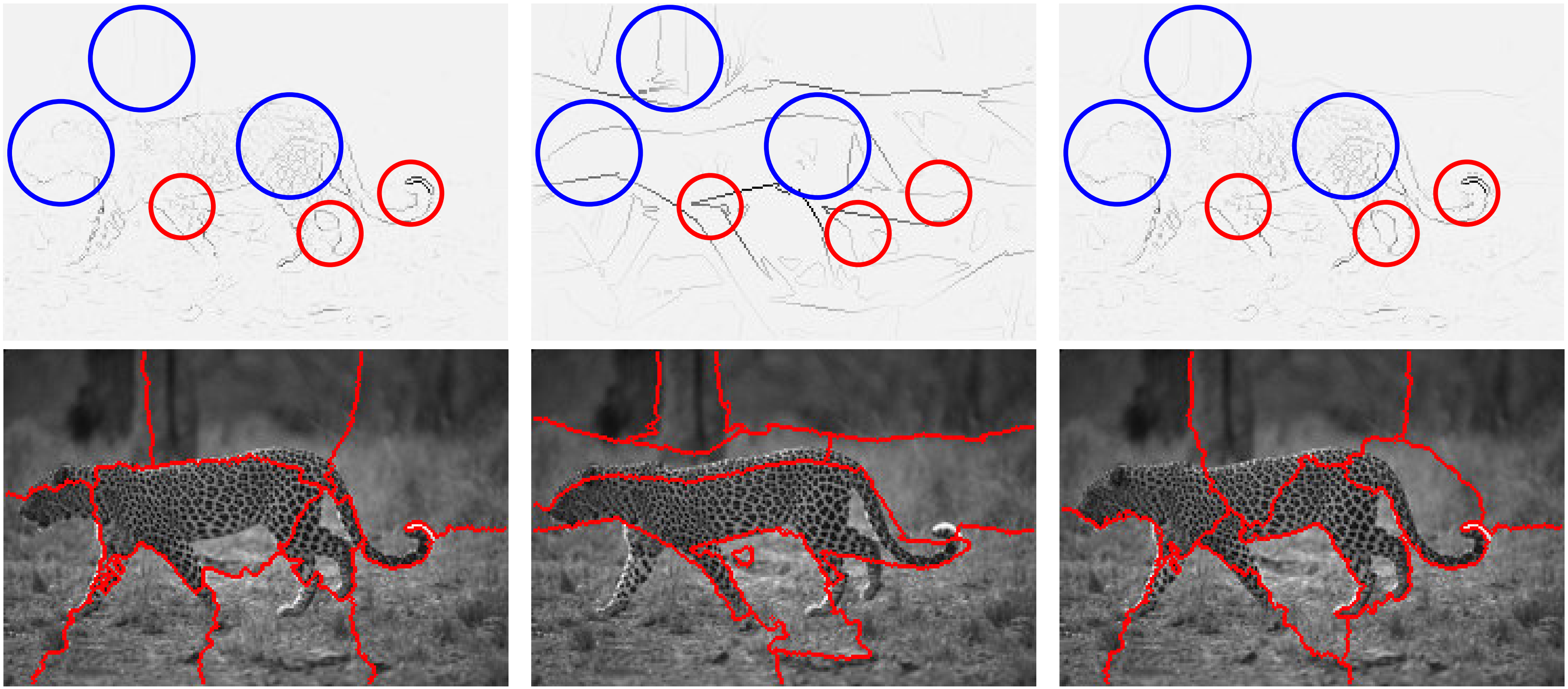
This work advocates:

one feature:	multiscale edges
one grouping cue:	intervening contours
one integration criterion:	average cuts of normalized affinity

Overview: Segmentation with Multiscale Edges



1. Image Feature: Multiscale Edges



small scale | large scale | optimal scale

1. Edges of small and large scales complement each other

   small $\Longrightarrow$ follow curves precisely; large $\Longrightarrow$ ignore textural variation

2. Resolving scale ambiguity at image feature level is premature

   optimal only for step edges in isolation; ill-defined at junctions, curves, abutting regions of various scales

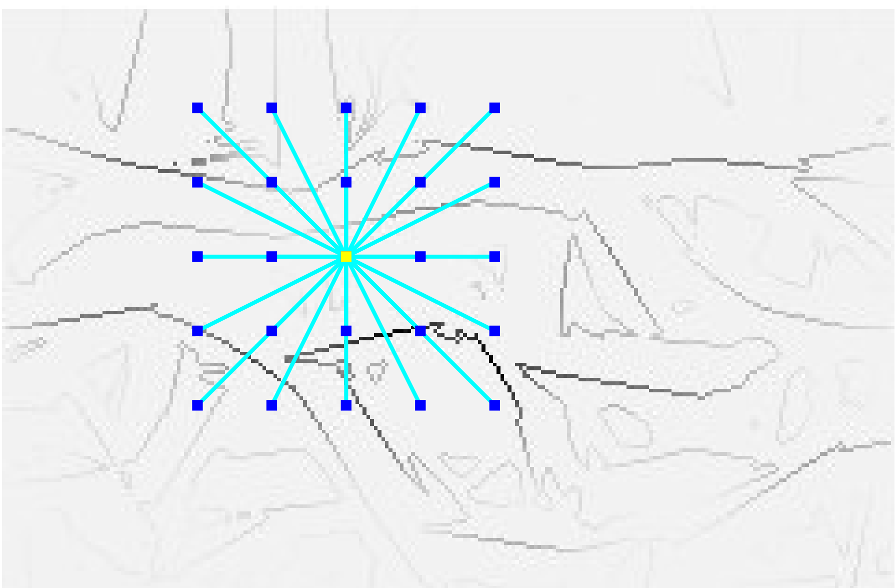
2. Pixel Grouping Cue: Multigrid Affinity

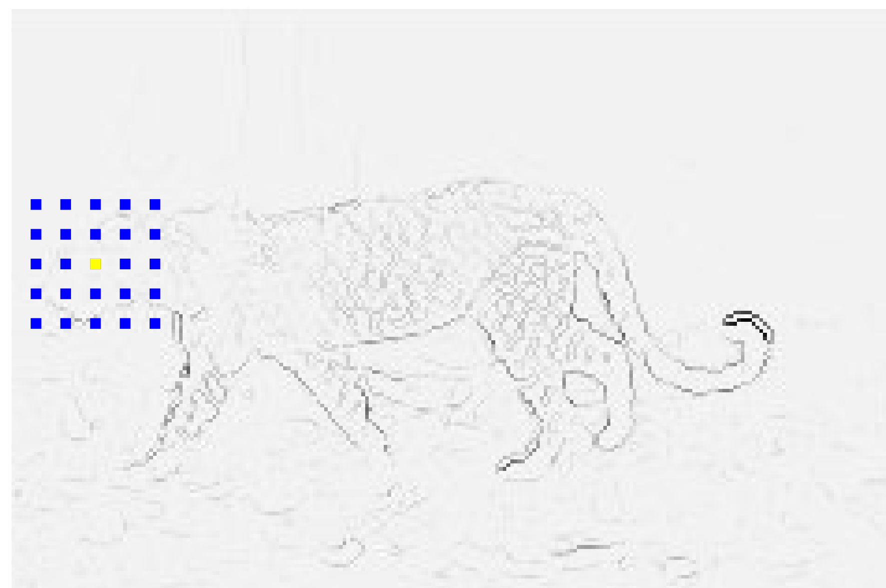
Intervening contour casts edges to grouping cues between their pixel supports.

$$A_{IC}(i,j) = \exp\left(-\frac{\max_{t \in \text{line}(i,j)} \text{edge-strength}(t)}{\sigma}\right)$$

Its range of applicability is bounded by leakage and localization uncertainty.

$$W(i,j;\text{grid}) = A_{IC}(i,j), \quad \text{distance}(i,j) \in [\text{certainty distance}, \text{neighbourhood radius}]$$





lowerbound from localization uncertainty

upperbound from leakage

3. Criterion: Average Cuts of Normalized Affinity

goodness of grouping

$$= \frac{1}{K} \sum_{l=1}^{K} \frac{\sum_{j \in \text{group } l} \text{proportion of node } j\text{'s links that are contained in group } l}{\text{number of nodes in group } l}$$

$$= \frac{1}{K} \sum_{l=1}^{K} \text{average normalized affinity for group } l$$

Properties:

duality: minimum cuts between groups $\Longleftrightarrow$ maximum connections within groups

efficiency: near-global optima through eigendecomposition

An analogy in democracy:

why normalized affinity: one person one vote on the same 0-1 scale, rich or poor

why average cuts: populous states do not dominate

Algorithm

Given: image I of N pixels,
filter parameter ρ, affinity parameter σ, neighbourhood radius r,
grid spacing parameter g, number of segments K

Step 1: Compute edges at multiple scales.

$E(\rho) = (I * F_o(\rho))^2 + (I * F_e(\rho))^2$.

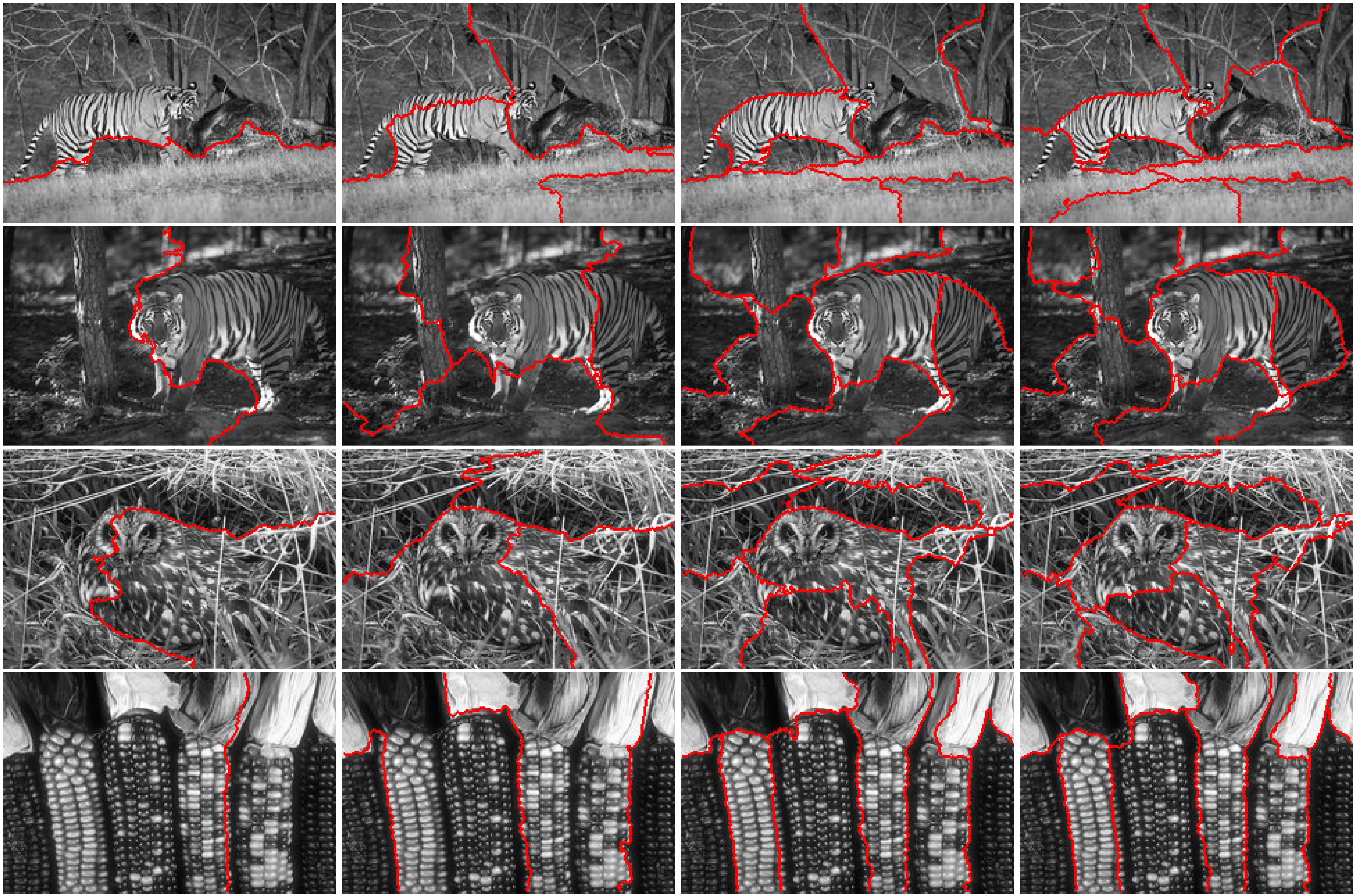
Step 2: Compute pixel affinity at multiple grids.

$t = 0$
For every scale ρ,
$d =$ certainty distance of filter ρ
For every grid spacing g,
$t = t + 1$
$W_t(i, j) = A_{IC}(i, j)$, distance$(i, j) = k \cdot g \cdot d$, $k \in [1, r]$, $j = 1 : N$.

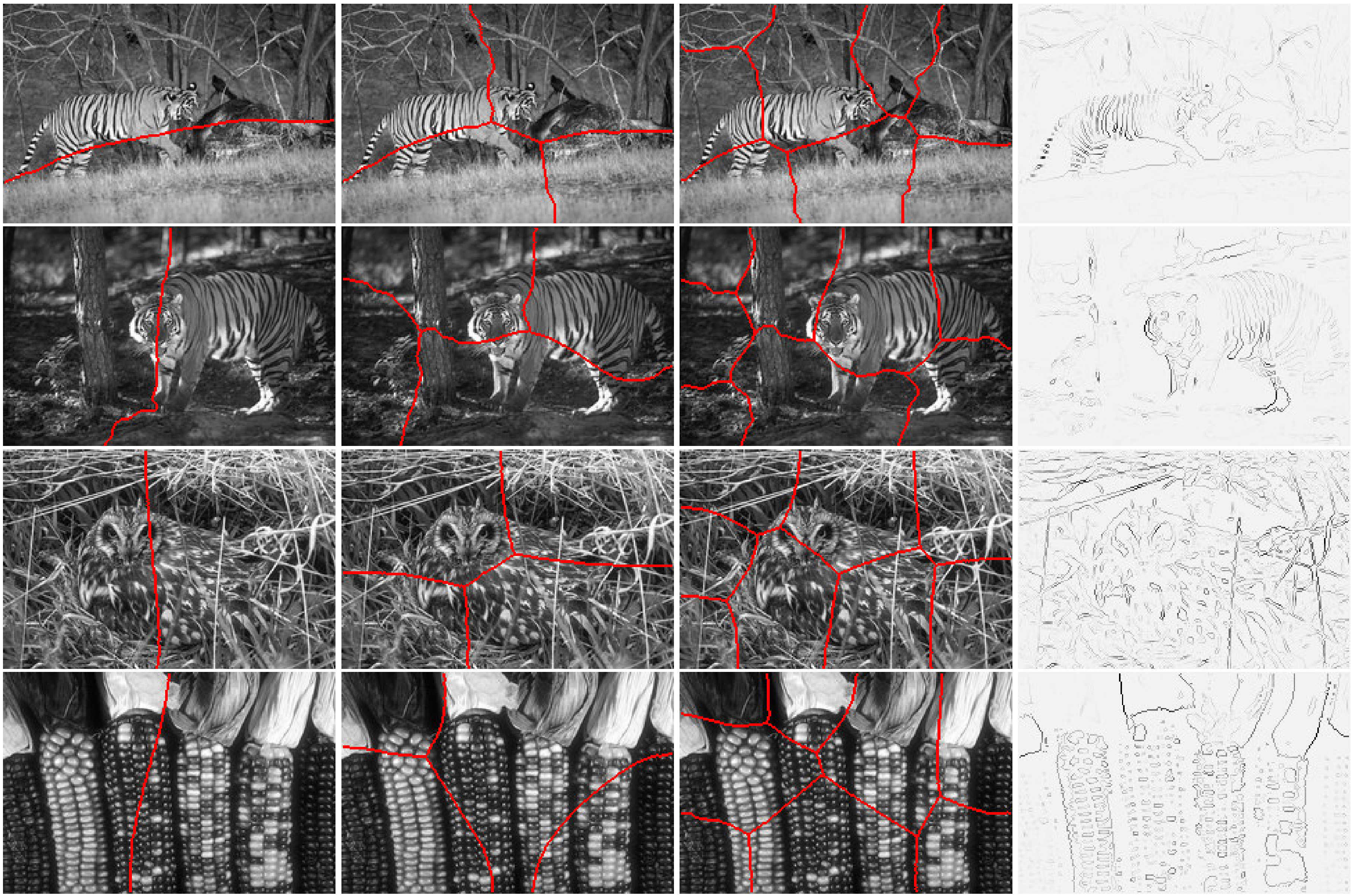
Step 3: Compute average cuts of normalized affinity.

$A = W_1 D_1^{-1} + \ldots + W_M D_M^{-1}$
$\bar{A} = A + A^T$
Solve for the first K eigenvectors V of $\bar{A}$
Obtain a discrete segmentation from V.

New: Average Cuts with Multiscale Edges



Old: Normalized Cuts with Optimal Edges

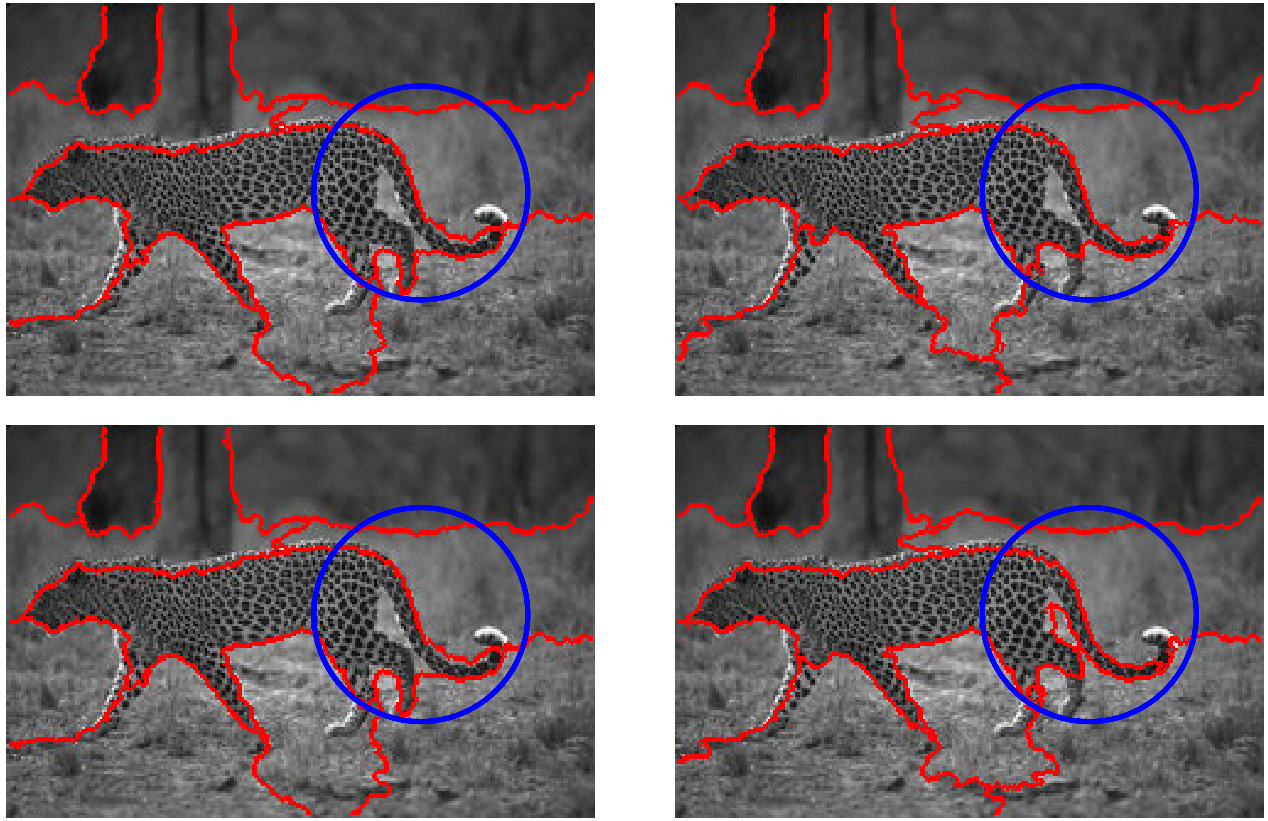


Advantages over Normalized Cuts Criterion

	un-normalized affinity	normalized affinity
	$A = W_1 + \ldots + W_M$	$A = W_1 D_1^{-1} + \ldots + W_M D_M^{-1}$

normalized cuts

average cuts



Average cuts of normalized affinity criterion has two advantages:

1. Straightforward interpretation of a simultaneous cut through multiple graphs.
2. Individual normalization of affinity promotes grouping cues according to scale.

Results on Articulated Body Configurations

Summary

Key insights:

1. Neither edges nor boundaries are single-scale phenomena.
2. Edges at all scales should be used without competition in scale-space.
3. Integration across scales must take the reliability of cues into account.
4. Multiscale edges are all we need to treat both texture and illusory contours.

New graph cuts approach to segmentation:

1. one feature, one cue, one criterion
2. Coarse to fine segmentations.
3. Simplified multiscale interactions.
4. Numerically fast and efficient.

Coming up:

hard examples on illusory contours (optimal scale, this work, new work)