TEXEL BASED TEXTURE SEGMENTATION

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PROBLEM STATEMENT

Given an arbitrary image, segment all texture subimages.

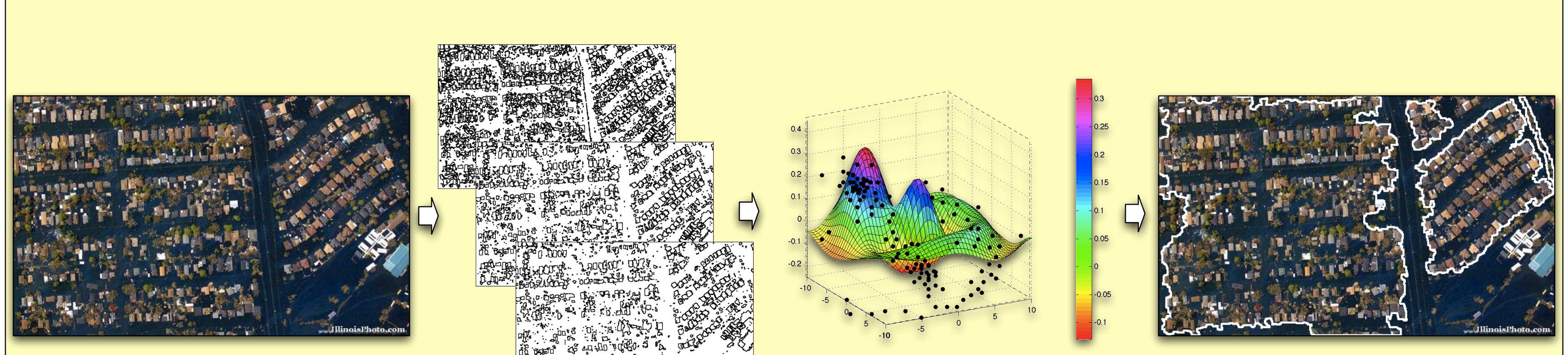
- Texture = Spatial repetition of texture elements, i.e., texels
- Texels are not identical, but only statistically similar to one another.
- Texel placement along the texture surface is not periodic, but only statistically uniform.
- Texels in the image are not homogeneous blobs or patches, but regions that may contain subregions.

RATIONALE

- Texels occupy image regions
- If the image contains texture
  - ⇒ Many regions will have similar properties
    - color, shape, layout of subregions,
    - orientation, relative displacements
  - ⇒ The pdf of region properties will have modes

Texture detection and segmentation ⇔ Detection of modes of the pdf of region properties

OVERVIEW OF OUR APPROACH



input image → multiscale segmentation → region pdf mode detection → texture detection and segmentation

CONTRIBUTIONS

- No assumptions about the pdf of texel properties
- Both appearance and placement of the texels are allowed to be *stochastic* and *correlated*
- New hierarchical, adaptive-bandwidth kernel to capture texel structural properties

MEANSHIFT FOR PDF MODE DETECTION

1) Define a feature space of region properties
2) Descriptor of each region = Data point in the feature space
3) Partition the feature space into bins by Voronoi tessellation
4) Run the meanshift with the new, hierarchical kernel
5) Regions under a pdf mode comprise the texture subimage

HIERARCHICAL, ADAPTIVE-BANDWIDTH KERNEL

- $\boldsymbol{x}$ - sample point
- N - number of points
- M - number of bins
- $|B_j|$ - volume of j-th bin
- $\boldsymbol{b}_j$ - representative of j-th bin
- n_j - number of points in j-th bin
- $\boldsymbol{H}_j$ - kernel width in j-th bin
- $\eta(j)$ - neighboring bins of j-th bin

pdf estimate $\hat{f}_B(\boldsymbol{x}) = \frac{1}{N}\sum_{j=1}^{M} n_j K(\boldsymbol{x}-\boldsymbol{b}_j;\boldsymbol{H}_j)$

<u>Theorem:</u>

$$\boldsymbol{H}_j \approx \sum_{i\in\eta(j)} \frac{3|B_i|(\boldsymbol{b}_i-\boldsymbol{b}_j)(\boldsymbol{b}_i-\boldsymbol{b}_j)^T}{|B_j|+\sum_{i'\in\eta(j)}|B_{i'}|}$$

$$K(\boldsymbol{x}_i-\boldsymbol{x}_j;\boldsymbol{H}_j) \triangleq$$

Gaussian kernel

$$K^{\mathrm{G}}(\boldsymbol{x}_i-\boldsymbol{x}_j;\boldsymbol{H}_j) \prod_{\text{matched subregions}} K^{\mathrm{G}}(\boldsymbol{x}_k-\boldsymbol{x}_l;\boldsymbol{H}_l),$$

$$\prod_{\text{matched subregions}} K^{\mathrm{G}}(\boldsymbol{x}_k-\boldsymbol{x}_l;\boldsymbol{H}_l) = \min_{\text{matching}(i,j)} \sum_{(k,l)\in\text{matching}(i,j)} (\boldsymbol{x}_k-\boldsymbol{x}_l)^T \boldsymbol{H}_l^{-1}(\boldsymbol{x}_k-\boldsymbol{x}_l).$$

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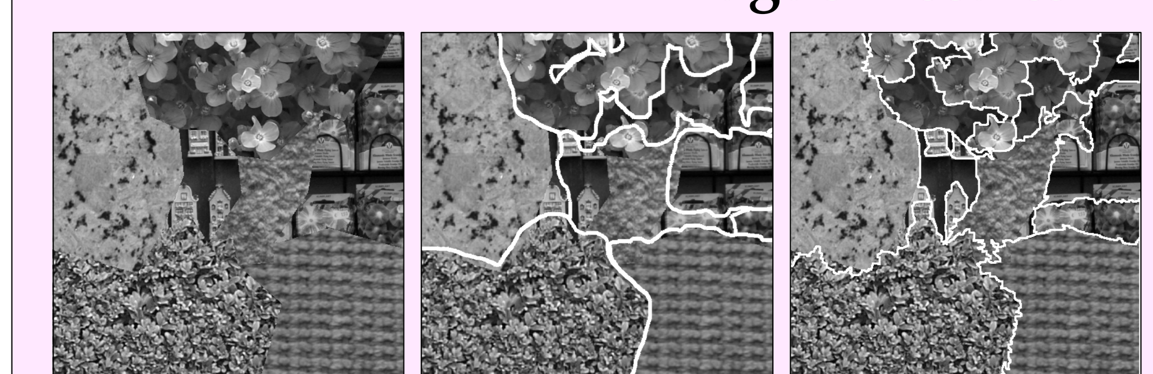
RESULTS

Aerial-produce images

Prague mosaics

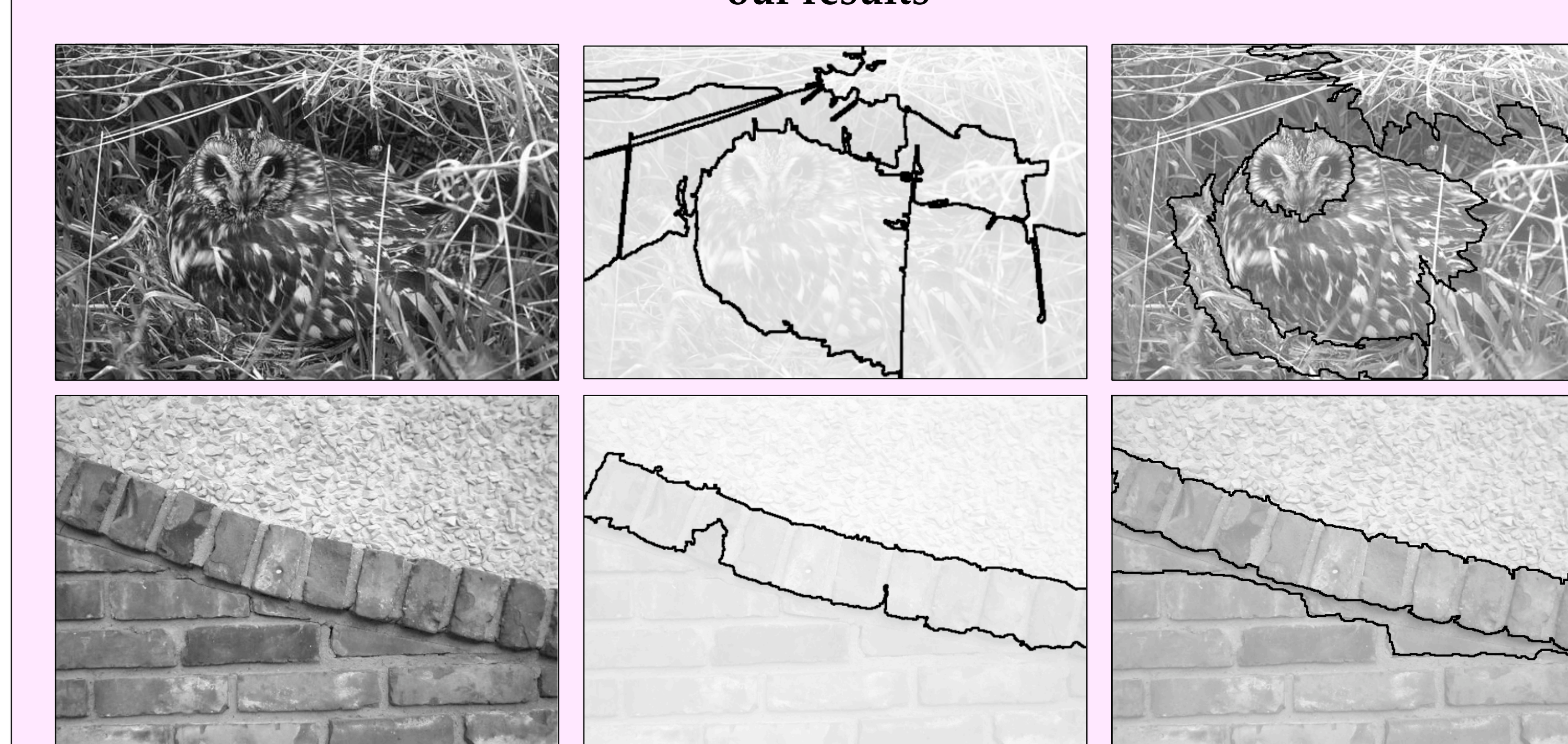


input image | [1] | our results

	[1]	Ours
Segm. accuracy	56.37%	59.13%
Over segm. error	11.93%	10.89%
Under segm. error	19.79%	18.79%

Berkeley segmentation dataset

our results



input image | [2] | our results

[1] M. Donoser and H. Bischof. Using covariance matrices for unsupervised texture segmentation. In ICPR, 2008.
[2] M. Galun, E. Sharon, R. Basri, and A. Brandt. Texture seg- mentation by multiscale aggregation of filter responses and shape elements. In ICCV, pages 716–723, 2003