
CS 129: Computational Photography
James Hays, Brown, Fall 2012

With slides from Alexei Efros, Jean Francois Lalonde, Derek Hoiem, and Antonio Torralba
Recap: Using lots of data!

Trick: If you have enough images, the dataset will contain very similar images that you can find with simple matching methods.
im2gps (Hays & Efros, CVPR 2008)

6 million geo-tagged Flickr images
How much can an image tell about its geographic location?
Today

Using lots of data to create new images

Input + Huge Dataset → Image Content from Similar Images

Huge Dataset:
- Images
- Associated Info

Image matching
Semantic Photo Synthesis

Huge Dataset
- Images
- Associated Info

Image description + image matching

Image Content from Similar Images

Semantic Photo Synthesis
CG2Real

Fake image! + Huge Dataset → Images, Associated Info → image matching → Textures from Similar Images

Photo Clip Art

Real image! + Huge Dataset

Images
Associated Info

image matching

Photographic “Objects” from similar images

Inserting objects into images
Inserting objects into images

[Debevec, ’98]
Inserting objects in images

Highly detailed geometry
Highly detailed materials
Very expensive

Realistic renderings
Expensive and impractical

[Debevec, ’98]
Alternative: Clip art

Easy, intuitive, cheap
Not realistic
Creating images (2-D)

Photo-realistic
Image-based rendering

Expensive and impractical

Photo Clip Art

?

Cheap and intuitive
Clip Art

Cartoon
“Photoshopping”
Inserting objects into images
Challenges

Insert THIS object: impossible!
The use of data

Insert SOME object: much easier!
The Google model

Database

Query

Results

Label objects in the images.

Sort the objects
Data source: LabelMe

Online (http://labelme.csail.mit.edu), user-contributed 170,000 objects in 40,000 images

Polygons and names

[Russell et al., 2005]
Data organization

Top-level categories (chosen manually, 16 total)
What should we match?
Camera parameters

Assume
- flat ground plane
- all objects on ground
- camera roll is negligible (consider pitch only)

Camera parameters: height and orientation
Human height distribution
1.7 +/- 0.085 m
(National Center for Health Statistics)

Car height distribution
1.5 +/- 0.19 m
(automatically learned)
Object heights

Database image

Pixel heights

Real heights

100 px

1.0 m

200 px

1.5 m

300 px

0.5 m
## Estimated object heights

<table>
<thead>
<tr>
<th>Object</th>
<th>Estimated average height (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Car</td>
<td>1.51</td>
</tr>
<tr>
<td>Man</td>
<td>1.80</td>
</tr>
<tr>
<td>Woman</td>
<td>1.67</td>
</tr>
<tr>
<td>Parking meter</td>
<td>1.36</td>
</tr>
<tr>
<td>Fire hydrant</td>
<td>0.87</td>
</tr>
</tbody>
</table>

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<tr>
<th>Height (m)</th>
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<th>Man</th>
<th>Woman</th>
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<th>Fire hydrant</th>
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</thead>
<tbody>
<tr>
<td>1.5 m</td>
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<td></td>
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<tr>
<td>1.0 m</td>
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</table>
What should we match?
Geometry is not enough
Illumination context

- Exact environment map is impossible
- Approximations [Khan et al., ‘06]

Database image

Environment map rough approximation
Illumination context

Database image

P(pixel|class)

CIE L* a* b* histograms

Automatic Photo PopupHoiem et al., SIGGRAPH ’00
Illumination nearest-neighbors
Other criteria: local context
Other criteria: segmentation

LabelMe contributors not always reliable
Segmentation quality

38 points / polygon

4 points / polygon
Other criteria: blur

Resolution: avoid up-sampling

x3 up-sampling
Recap

Phase I: Database annotation

Object properties (used for sorting the database)

<table>
<thead>
<tr>
<th>Label</th>
<th>Cluster</th>
<th>3-D height</th>
<th>Camera</th>
<th>Illumination context</th>
<th>Local context</th>
<th>Segmentation</th>
<th>Blur</th>
</tr>
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Phase II: Object insertion
Let’s insert an object!

Poor user-provided segmentations
Noticeable seams
Seams

Input

Destination image

Result

Visible seam!

[Perez et al., 2003]
Poisson blending: idea

Enforce boundary color (seamless result)

Enforce same gradient than input

[1] Perez et al., 2003
Still not right!

Not so sensitive to shadow direction [Cavanagh, 2005]
Street accident
Painting
Alley
Failure cases

- Porous objects
- Shadow transfer
Failure cases
The Dangers of Data
Bias

Internet is a tremendous repository of visual data (Flickr, YouTube, Picasa, etc.)
But it’s not random samples of visual world
Many sources of bias:
  • Sampling bias
  • Photographer bias
  • Social bias
Flickr Paris
Real Paris
Real Notre Dame
Sampling Bias

People like to take pictures on vacation
Sampling Bias

People like to take pictures on vacation
Photographer Bias

People want their pictures to be recognizable and/or interesting

VS.
Photographer Bias

People follow photographic conventions

vs.
<table>
<thead>
<tr>
<th>Social Bias</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="Little Leaguer" /></td>
</tr>
<tr>
<td><img src="image3" alt="The Graduate" /></td>
</tr>
</tbody>
</table>

“100 Special Moments” by Jason Salavon
Social Bias

Mildred and Lisa

Source: U.S. Social Security Administration

Gallagher et al CVPR 2008
Social Bias
Reducing / Changing Bias

Autonomous capture methods can reduce / change bias

- But it won’t go away completely

Sometimes you can just pick your data to suit your problem, but not always…
Overview

- Image description
- CG image
- Real image

Huge Dataset

- Images
- Associated information

image matching

- Image Content
- Textures
- Photographic "objects"