Programming Project #1

- Prokudin-Gorskii’s Color Photography (1907)
Programming Project #1

• Align R, G, B images (Due 2/16/2022)
Programming Project #1

• How to compare R,G,B channels?
• No right answer
  – Sum of Squared Differences (SSD):
    \[ \text{ssd}(u,v) = \sum_{(x,y) \in N} [I(u+x, v+y) - P(x, y)]^2 \]
  – Normalized Correlation (NCC):
    \[ \text{ncc}(u,v) = \frac{\sum_{(x,y) \in N} |I(u+x, v+y) - \bar{I}| |P(x, y) - \bar{P}|}{\sqrt{\sum_{(x,y) \in N} [I(u+x, v+y) - \bar{I}]^2 \sum_{(x,y) \in N} [P(x, y) - \bar{P}]^2}} \]
Review: Global/Local warping

- Prokudin-Gorskii’s Color Photography (1907)
Review: Global/Local warping

Global vs. Local warping
• Parameter sharing

Dense vs. sparse warping
• Degree of freedom
• Interpolation vs. curve fitting?

Triangulation vs. Moving Least Squares
• Piece-wise function
• Spatially-varying objective functions
Face Warping Demo
Data-Driven Graphics

Jun-Yan Zhu

16-726 Learning-based Image Synthesis, Spring 2022
Data-Driven Graphics

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Subject-specific Data

Photos of Coliseum

Portraits of Bill Clinton
Much of Captured World is “generic”
Generic Data

street scenes

Food plates

faces

pedestrians
Big Visual Data

- **flickr**: 6 billion images
- **YouTube**: 100 hours uploaded per minute
- **3.5 trillion photographs**
- **Imgur**: 1 billion images served daily
- **Facebook**: 70 billion images
The Internet as a Data Source

- Social Networking Sites (e.g., Facebook, Snapchat)
- Image Search Engines (e.g., Google, Bing)
- Photo Sharing Sites (e.g., Instagram, Flickr, Adobe Stock)
- Computer Vision Databases (e.g., ImageNet, Places, OpenImages)
Too Big for Humans

Digital Dark Matter

[Perona 2010]
Big issues

• What is out there on the Internet? How do we get it? What can we do with it?
• How do we compute distances between images?
Is Big Visual Data useful?

A motivating example...
Scene Matching for Image Completion
The Algorithm
Scene Matching
Scene Descriptor
Scene Descriptor
Scene Descriptor

(Oliva and Torralba 2001)
2 Million Flickr Images
Context Matching
Graph cut + Poisson blending.
Image Blending
Poisson Image Blending

More details in the later lectures.
More results
Why does it work?
Nearest neighbors from a collection of 20 thousand images
Nearest neighbors from a collection of 2 million images
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.
Semantic Photo Synthesis

Semantic Photo Synthesis [EG’06]

Semantic Photo Synthesis
Photo Clip Art [SIGGRAPH 2007]
Inserting a single object -- still very hard!

- object size, orientation
- scene illumination

[Lalonde et al, SIGGRAPH 2007]
Photo Clip Art

Use database to find well-fitting object

Lalonde et al, SIGGRAPH 2007
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

Automatic Photo Popup
Hoiem et al., SIGGRAPH ’05

P(pixel|class)

CIE L*a*b* histograms
Illumination nearest-neighbors
Street accident
Bridge
Painting
Alley
Failure cases

Porous objects

Shadow transfer
Failure cases
Review (Data-driven Graphics)

• How to find images given a user query?
  – Image Retrieval (Gist descriptor? Deep learning?)
  – Big data helps!

• How to combine images?
  – Image blending (Poisson Equation)
How to Combine Images?

• Image Blending/Compositing:
  – Each piece comes from a different image.
  – Need to hide the boundary
Sketch2Photo

User Sketch + Huge Dataset

Images + Associated Info

image matching

Image Content from Similar Images
Sketch2Photo

Sketch-based image retrieval + image blending

User Input

Database images

Output


Shape retrieval [Belongie et al. PAMI 2002]

Only based on the extracted contour
How to Combine Images?

• **Image Blending/Compositing:**
  – Each piece comes from a different image.
  – Need to hide the boundary

• **Image Averaging**
  – Each pixel is a combination of multiple pixels from different images.
  – Special case: Cross-Dissolve (two images)
Image Averaging

Multiple Individuals


Sir Francis Galton
1822-1911

Composite
Average Images in Art

“60 passagers de 2e classe du metro, entre 9h et 11h” (1985)
Krzysztof Pruszkowski

“Dynamism of a cyclist” (2001)
James Campbell

“Spherical type gasholders” (2004)
Idris Khan
“100 Special Moments” (2004) by Jason Salavon

Newlyweds  Little Leaguer  Kids with Santa
Not so simple...

Jason Salavon
“Kids with Santa”

Google query result:
“kids with Santa”

Automatic Average
Why Difficult?

Google results

Visual Modes

Misaligned
“Object-Centric Averages” (2001) by Antonio Torralba

Manual Annotation and Alignment

Average Image
With Alignment

Google results

Visual Modes

Misaligned

Aligned
Goal:

An interactive system to rapidly explore and align a large image collection using *image averaging*
Weighted Averages Overview

Image Collection \( \{I_1 \ldots I_N\} \) (e.g. “Kids with Santa” images)

Alignment

Average \( I_{avg} \)

\[
I_{avg} = \frac{\sum_{i=1}^{N} \sum_{i=1}^{N} I_i}{I_i}
\]

Image Weights \( \{s_1 \ldots s_N\} \)
Sketching Brush

Image Collection \( \{I_1 \ldots I_N\} \)

Average

Weight \( s_i + \text{similarity}(\cdot, \cdot) \)
Coloring Brush

Image Collection \( \{I_1 \cdots I_N\}_I \)

Average

Weight

\[ s_i + \text{similarity}(\_\_, \_\_) \]
Explorer Brush: Select a Local Mode

\[ N \text{ Image Batches} \]

Local Visual Modes

\[ s_i = s_i + \text{similarity}(\cdot, \cdot) \]

Average Window

Discriminative Patch Discovery

[Doersch et al. 2012]
Weighted Averages + Alignment

Image Collection \( \{I_1 \cdots I_N\} \) (e.g. “Kids with Santa” images)

Average \( I_{avg} \)

Image Weights \( \{s_1 \cdots s_N\} \)
Image Alignment

User Edit

Image 1

Image 2

Average Image

Mean Position
Different Cat Breeds (Simple Average)

Abyssinian  Sphynx  Birman  Bombay  Egyptian Mau  Ragdoll

British Shorthair  Persian  Maine Coon  Russian Blue  Siamese  Bengal

Data from [Parkhi et al. 2012]
Different Cat Breeds (Our Result)

- Abyssinian
- Sphynx
- Birman
- Bombay
- Egyptian Mau
- Ragdoll
- British Shorthair
- Persian
- Maine Coon
- Russian Blue
- Siamese
- Bengal

Data from [Parkhi et al. 2012]
Application: Online shopping
AverageExplorer

User input + Huge Dataset

Images

Patch Dictionary

image matching

Aligned Average from Similar Images
ShadowDraw

Bad sketch! + Huge Dataset

Images

Contour Dictionary

image matching

Contours from Similar Images
THANK YOU!

16-726, SPRING 2022

HTTPS://LEARNING-IMAGE-SYNTHESIS.GITHUB.IO/SP22/