Image Pyramids and Blending

15-463: Computational Photography
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Image Pyramids

Idea: Represent NxN image as a “pyramid” of 1x1, 2x2, 4x4,..., $2^k \times 2^k$ images (assuming $N = 2^k$)

 Known as a **Gaussian Pyramid** [Burt and Adelson, 1983]
  - In computer graphics, a *mip map* [Williams, 1983]
  - A precursor to *wavelet transform*
A bar in the big images is a hair on the zebra’s nose; in smaller images, a stripe; in the smallest, the animal’s nose.

Figure from David Forsyth
What are they good for?

**Improve Search**
- Search over translations
  - Like homework
  - Classic coarse-to-fine strategy
- Search over scale
  - Template matching
  - E.g. find a face at different scales

**Precomputation**
- Need to access image at different blur levels
- Useful for texture mapping at different resolutions (called mip-mapping)

**Image Processing**
- Editing frequency bands separately
- E.g. image blending…
Gaussian pyramid construction

Repeat
  • Filter
  • Subsample

Until minimum resolution reached
  • can specify desired number of levels (e.g., 3-level pyramid)

The whole pyramid is only 4/3 the size of the original image!
Image sub-sampling

Throw away every other row and column to create a 1/2 size image - called *image sub-sampling*
Image sub-sampling

1/2

1/4 (2x zoom)

1/8 (4x zoom)

Why does this look so bad?
Sampling

Good sampling:
• Sample often or,
• Sample wisely

Bad sampling:
• see aliasing in action!
Really bad in video

Imagine a spoked wheel moving to the right (rotating clockwise). Mark wheel with dot so we can see what’s happening.

If camera shutter is only open for a fraction of a frame time (frame time = 1/30 sec. for video, 1/24 sec. for film):

Without dot, wheel appears to be rotating slowly backwards! (counterclockwise)
Alias: n., an assumed name

Picket fence receding into the distance will produce aliasing...

WHY?

Input signal:

Matlab output:

\[ x = 0:.05:5; \text{ imagesc}(\sin((2.^x).*x)) \]

Aj-aj-aj: Alias!

Not enough samples
Gaussian pre-filtering

Solution: filter the image, *then* subsample

- Filter size should double for each $\frac{1}{2}$ size reduction. Why?
Subsampling with Gaussian pre-filtering

Solution: filter the image, \textit{then} subsample

- Filter size should double for each $\frac{1}{2}$ size reduction. Why?
- How can we speed this up?
Compare with...

1/2

1/4 (2x zoom)

1/8 (4x zoom)
Image Blending
Feathering

Encoding transparency

\[ I(x,y) = (\alpha R, \alpha G, \alpha B, \alpha) \]

\[ I_{\text{blend}} = I_{\text{left}} + I_{\text{right}} \]
Affect of Window Size

(left) 1
  0

(right) 1
  0

left

right
Affect of Window Size
Good Window Size

“Optimal” Window: smooth but not ghosted
What is the Optimal Window?

To avoid seams
- window >= size of largest prominent feature

To avoid ghosting
- window <= 2*size of smallest prominent feature

Natural to cast this in the *Fourier domain*
- largest frequency <= 2*size of smallest frequency
- image frequency content should occupy one “octave” (power of two)
What if the Frequency Spread is Wide

Idea (Burt and Adelson)

• Compute $F_{\text{left}} = \text{FFT}(I_{\text{left}})$, $F_{\text{right}} = \text{FFT}(I_{\text{right}})$
• Decompose Fourier image into octaves (bands)
  – $F_{\text{left}} = F_{\text{left}}^1 + F_{\text{left}}^2 + \ldots$
• Feather corresponding octaves $F_{\text{left}}^i$ with $F_{\text{right}}^i$
  – Can compute inverse FFT and feather in spatial domain
• Sum feathered octave images in frequency domain

Better implemented in *spatial domain*
What does blurring take away?
What does blurring take away?

smoothed (5x5 Gaussian)
High-Pass filter

smoothed – original
Band-pass filtering

Gaussian Pyramid (low-pass images)
Laplacian Pyramid

How can we reconstruct (collapse) this pyramid into the original image?
Pyramid Blending

Left pyramid  blend  Right pyramid
Pyramid Blending
laplacian level 4

laplacian level 2

laplacian level 0

left pyramid
right pyramid
blended pyramid
Laplacian Pyramid: Blending

General Approach:

1. Build Laplacian pyramids $LA$ and $LB$ from images $A$ and $B$
2. Build a Gaussian pyramid $GR$ from selected region $R$
3. Form a combined pyramid $LS$ from $LA$ and $LB$ using nodes of $GR$ as weights:
   - $LS(i,j) = GR(i,j) \times LA(i,j) + (1-GR(i,j)) \times LB(i,j)$
4. Collapse the $LS$ pyramid to get the final blended image
Blending Regions
Season Blending (St. Petersburg)
Season Blending (St. Petersburg)
Simplification: Two-band Blending

Brown & Lowe, 2003

- Only use two bands: high freq. and low freq.
- Blends low freq. smoothly
- Blend high freq. with no smoothing: use binary mask
2-band Blending

Low frequency ($\lambda > 2$ pixels)

High frequency ($\lambda < 2$ pixels)
Linear Blending
2-band Blending
Gradient Domain

In Pyramid Blending, we decomposed our image into 2\textsuperscript{nd} derivatives (Laplacian) and a low-res image.

Let us now look at 1\textsuperscript{st} derivatives (gradients):

- No need for low-res image
  - captures everything (up to a constant)

- Idea:
  - Differentiate
  - Blend
  - Reintegrate
Gradient Domain blending (1D)

Two signals

Regular blending

Blending derivatives
Gradient Domain Blending (2D)

Trickier in 2D:

- Take partial derivatives $dx$ and $dy$ (the gradient field)
- Fiddle around with them (smooth, blend, feather, etc)
- Reintegrate
  - But now $\text{integral}(dx)$ might not equal $\text{integral}(dy)$
- Find the most agreeable solution
  - Equivalent to solving Poisson equation
  - Can use FFT, deconvolution, multigrid solvers, etc.
Comparisons: Levin et al, 2004

Pyramid blending
Feathering

Pyramid blending on the gradients
GIST1
Perez et al, 2003

Limitations:

- Can’t do contrast reversal (gray on black -> gray on white)
- Colored backgrounds “bleed through”
- Images need to be very well aligned
Don’t blend, CUT!

Moving objects become ghosts

So far we only tried to blend between two images. What about finding an optimal seam?
Davis, 1998

Segment the mosaic

- Single source image per segment
- Avoid artifacts along boundaries
  - Dijkstra’s algorithm
Efros & Freeman, 2001

- Random placement of blocks
- Neighboring blocks constrained by overlap
- Minimal error boundary cut
Minimal error boundary

overlapping blocks

vertical boundary

overlap error

min. error boundary
Graphcuts

What if we want similar “cut-where-things-agree” idea, but for closed regions?

- Dynamic programming can’t handle loops
Graph cuts
(simple example à la Boykov&Jolly, ICCV'01)

Minimum cost cut can be computed in polynomial time
(max-flow/min-cut algorithms)
Kwatra et al, 2003

Actually, for this example, DP will work just as well…
Lazy Snapping (Li et al., 2004)

Interactive segmentation using graphcuts
Putting it all together

Compositing images

• Have a clever blending function
  – Feathering
  – blend different frequencies differently
  – Gradient based blending

• Choose the right pixels from each image
  – Dynamic programming – optimal seams
  – Graph-cuts

Now, let’s put it all together:

• Interactive Digital Photomontage, 2004 (video)
Interactive Digital Photomontage

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Brian Curless, David Salesin, Michael Cohen