

Gaussian & Laplacian Pyramid - A 1D Example Blending Algorithm

Slides by Yawen Ma

Based on Sam Hasinoff's tutorial notes

Pyramid Blending



(d)



(h)



(l)

The 5-tap 1D

- Symmetric
 - $\hat{w} = [a \ b \ c \ b \ a]$
- Same weight for sum odd and sum even location
 - $a + c + a = b + b = 0.5$
 - So $\hat{w} = [0.25 - \frac{c}{2}, 0.25, c, 0.25, 0.25 - \frac{c}{2}]$

In this example we use $c=0.4$

$$\text{So } \hat{w} = [0.05, 0.25, 0.40, 0.25, 0.05] = \frac{1}{20} [1 \ 5 \ 8 \ 5 \ 1]$$

Consider a $9=2^3+1$ pixel example image

$$G_{k-1} = [6 \ 8 \ 1 \ 5 \ 1 \ 9 \ 5 \ 7 \ 9]$$

- let's find $G_k = \text{REDUCE}(G_{k-1})$
 - It will have ~half as many pixels, more specifically $5=2^2+1$ pixels
 - we only need to compute the odd pixels since we'll throw the rest away ..
"x" below means shouldn't/cannot compute

$$G_{k-1} = [6 \ 8 \ 1 \ 5 \ 1 \ 9 \ 5 \ 7 \ 9]$$

$$G_k = [? \ x \ ? \ x \ ? \ x \ ? \ x \ ?]$$

(this is just convolution with \hat{w} but we only need to compute this convolution for the odd pixels)

Consider a $9=2^3+1$ pixel example image

$$G_{k-1} = [6 \ 8 \ 1 \ 5 \ 1 \ 9 \ 5 \ 7 \ 9]$$

- let's find $G_k = \text{REDUCE}(G_{k-1})$

$$G_{k-1} = [6 \ 8 \ 1 \ 5 \ 1 \ 9 \ 5 \ 7 \ 9]$$

$$G_k = [? \ x \ ? \ x \ ? \ x \ ? \ x \ ?]$$

$$\begin{aligned} \text{eg. } G_k(3) &= [1 \ 5 \ 1 \ 9 \ 5] * \frac{1}{20} [1 \ 5 \ 8 \ 5 \ 1] \\ &= \frac{1}{20} (1 + 25 + 8 + 45 + 5) \\ &= 84/20 \\ &= 4.2 \end{aligned}$$

$$G_k(2)?$$

Consider a $9=2^3+1$ pixel example image

$$G_{k-1} = [6 \ 8 \ 1 \ 5 \ 1 \ 9 \ 5 \ 7 \ 9]$$

- let's find $G_k = \text{REDUCE}(G_{k-1})$

$$G_{k-1} = [6 \ 8 \ 1 \ 5 \ 1 \ 9 \ 5 \ 7 \ 9]$$

$$G_k = [? \times \ ? \times \ ? \times \ ? \times \ ?]$$

$$\begin{aligned} \text{eg. } G_k(1) &= [x \ x \ 6 \ 8 \ 1] * \frac{1}{20} [1 \ 5 \ 8 \ 5 \ 1] \\ &= [6 \ 8 \ 1] * \frac{1}{14} [8 \ 5 \ 1] \quad [\text{reweighted}] \\ &= \frac{1}{14} (48 + 40 + 1) \\ &= 89/14 \\ &= 6.4 \end{aligned}$$

$$G_k(5)?$$

Consider a $9=2^3+1$ pixel example image

$$G_{k-1} = [6 \ 8 \ 1 \ 5 \ 1 \ 9 \ 5 \ 7 \ 9]$$

- let's find $G_k = \text{REDUCE}(G_{k-1})$

$$G_{k-1} = [6 \ 8 \ 1 \ 5 \ 1 \ 9 \ 5 \ 7 \ 9]$$

$$G_k = [? \ x \ ? \ x \ ? \ x \ ? \ x \ ?]$$

after computing everything we get

$$G_k = [6.4, 4.0, 4.2, 6.5, 8.0]$$

EXPAND([6.4, 4.0, 4.2, 6.5, 8.0])

- this is up-sampling a smaller image, ~doubling its resolution ..
- conceptually the reverse of the REDUCE function
- it will have the same number of pixels as G_{k-1} , $9=3^2+1$ pixels
- we line things up and apply the same kernel as before, in the opposite direction, being careful to "reweight" the kernel so it sums to 1, given that ~half the pixels from the source G_k will be missing.

$$G_k = [6.4 \times 4.0 \times 4.2 \times 6.5 \times 8.0]$$

$$\text{EXPAND}(G_k) = [? \quad ? \quad ? \quad ? \quad ? \quad ? \quad ? \quad ? \quad ?]$$

EXPAND([6.4, 4.0, 4.2, 6.5, 8.0])

$$G_k = [6.4 \times 4.0 \times 4.2 \times 6.5 \times 8.0]$$

$$\text{EXPAND}(G_k) = [\text{?} \text{ ?} \text{ ?} \text{ ?} \text{ ?} \text{ ?} \text{ ?} \text{ ?}]$$

$$\begin{aligned} \text{eg. EXPAND}(G_k)(5) &= [4.0 \times 4.2 \times 6.5] * \frac{1}{20} [1 \ 5 \ 8 \ 5 \ 1] \\ &= [4.0 \ 4.2 \ 6.5] * \frac{1}{10} [1 \ 8 \ 1] \quad [\text{reweighted}] \\ &= 4.4 \end{aligned}$$

$$\begin{aligned} \text{eg. EXPAND}(G_k)(4) &= [\times 4.0 \times 4.2 \times] * \frac{1}{20} [1 \ 5 \ 8 \ 5 \ 1] \\ &= [4.0 \ 4.2] * \frac{1}{10} [5 \ 5] \quad [\text{reweighted}] \\ &= 4.1 \end{aligned}$$

EXPAND([6.4, 4.0, 4.2, 6.5, 8.0])

G_k = [6.4 x 4.0 x 4.2 x 6.5 x 8.0]

EXPAND(G_k) = [? ? ? ? ? ? ? ?]

eg. EXPAND(G_k)(1) = [x x 6.4 x 4.0] * $\frac{1}{20}$ [1 5 8 5 1]

= [6.4 4.0] * $\frac{1}{9}$ [8 1] [reweighted]

= 6.1

EXPAND([6.4, 4.0, 4.2, 6.5, 8.0])

G_k = [6.4 x 4.0 x 4.2 x 6.5 x 8.0]

EXPAND(G_k) = [6.1, 5.2, 4.3, 4.1, 4.4, 5.4, 6.4, 7.3, 7.8]

We started with

G_{k-1} = [6 8 1 5 1 9 5 7 9]

2D Case

- the 2D kernel function is separable and symmetric,
 - ie. $w(m,n) = \hat{w}(m) * \hat{w}(n)$
- so we can convolve the 1D \hat{w} first across rows, and then across columns (or vice versa) ... this will give the same result as convolving with the 2D kernel w directly

e.g. REDUCE for a 9x9 image

- REDUCE across rows to get a 9x5 image
- then REDUCE across columns to get a 5x5 image

e.g. EXPAND for a 5x5 image

- EXPAND across rows to get a 5x9 image
- then EXPAND across columns to get a 9x9 image

Compute the pyramids

To compute the Gaussian pyramid:

- $G_0 = I$ [original image]
- $G_k = \text{REDUCE}(G_{k-1})$ [successively blur/reduce resolution]
- G_N [stop when the image is 1x1, or earlier]

To compute the Laplacian pyramid:

- $L_N = G_N$ [base case, use the smallest Gaussian pyramid image]
- $L_k = G_k - \text{EXPAND}(G_{k+1})$ [detail/difference between successive Gaussian pyramid levels]

Blending algorithm

Input: images A, B & (binary) mask M that specifies the blend (0=A,1=B)

(pad everything to make them powers of 2 (+ 1), $(2^{N+1}) \times (2^{N+1})$)

- -> A & B's Laplacian pyramids AL_0, AL_1, \dots, AL_N & BL_0, BL_1, \dots, BL_N
- -> M's Gaussian pyramid MG_0, MG_1, \dots, MG_N
- compute a Laplacian pyramid for the result, S, using linear interpolation, for every pyramid level k,

$$SL_k(r, c) = (1 - MG_k(r, c)) * AL_k(r, c) + MG_k(r, c) * BL_k(r, c)$$

(we're simply doing linear interpolation over every pixel, with a blend mask given at different levels of detail)

Reconstitute the full-resolution image for S, by computing

- $SG_N = SL_N$
- $SG_k = SL_k + \text{EXPAND}(SG_{k+1})$

$$S = SG_0$$