

# Content-Adaptive Image Downscaling

## Supplementary Document

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|----------------|--|
| $(w_i, h_i)$   | input ( <i>high resolution</i> ) image dimensions  |
| $(w_o, h_o)$   | output ( <i>low resolution</i> ) image dimensions  |
| $(x_k, y_k)$   | 2D kernel indices; $(x_k, y_k) = (k \bmod w_o + \frac{1}{2}, \lfloor k/w_o \rfloor + \frac{1}{2})$   |
| $(r_x, r_y)$   | input/output dimension ratios; $(r_x, r_y) = (w_i/w_o, h_i/h_o)$   |
| $k, n$         | kernel indices; $k, n \in [0, w_o \cdot h_o - 1]$  |
| $\mu_k$        | spatial mean   |
| $\Sigma_k$     | spatial covariance   |
| $\mathbf{v}_k$ | color mean   |
| $\sigma_k$     | color variance   |
| $R_k$          | set of pixel indices where kernel $k$ can become non-zero;<br>$R_k = \{x + yw_i \mid 0 \leq x < w_i, 0 \leq y < h_i,  x - x_k  < 2r_x,  y - y_k  < 2r_y\}$ |
| $N_k^4$        | Set of indices of the 4-neighbors of kernel $k$  |
| $N_k^8$        | Set of indices of the 8-neighbors of kernel $k$  |
| $i$            | pixel index; $i \in [0, w_i \cdot h_i - 1]$  |
| $\mathbf{p}_i$ | pixel location; $\mathbf{p}_i = (i \bmod w_i, \lfloor i/w_i \rfloor)$  |
| $\mathbf{c}_i$ | CIELAB color of pixel $i$  |
| $w_k(i)$       | Value of kernel $k$ at pixel $i$   |
| $\gamma_k(i)$  | Value of <i>normalized</i> kernel $k$ at pixel $i$   |

**Figure 1:** Symbols used throughout the paper and in the pseudocode

## 1 Pseudocode

This document provides commented pseudocode for the algorithm described in the main paper, published in SIGGRAPH Asia 2013. Refer to Figure 1 for a list and explanations of symbols. The code here is complete and efficient, e.g. kernel computations are clamped to ranges where they take on non-zero values. However, for maximum clarity we did not always combine all loops wherever possible.

The function  $\text{clamp}(x, \minVal, \maxVal)$  constrains the scalar  $x$  to lie within the range specified. Similarly, the function  $\text{clampBox}(\mathbf{v}, \mathbf{Box})$  constrains the 2-vector  $\mathbf{v}$  to lie within  $\mathbf{Box}$ . The function  $\text{SVD}(\Sigma)$  performs singular value decomposition.

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// The main program
1: procedure DOWNSCALING
2:   INITIALIZE
3:   loop
4:     E-STEP
5:     M-STEP
6:     C-STEP
7:     if no changes in last M-Step or C-Step then return
8:   end loop
9: end procedure

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// Initialize all variables
10: procedure INITIALIZE
11:   for all  $k$  do
12:      $\mu_k \leftarrow (x_k, y_k)^\top$ 
13:      $\Sigma_k \leftarrow \begin{bmatrix} r_x/3 & 0 \\ 0 & r_y/3 \end{bmatrix}$ 
14:      $\mathbf{v}_k \leftarrow (\frac{1}{2}, \frac{1}{2}, \frac{1}{2})^\top$ 
15:      $\sigma_k \leftarrow 10^{-4}$ 
16:   end for
17: end procedure

// Expectation step
18: procedure E-STEP
19:   // Compute all kernels
20:   for all  $k$  do
21:     for all  $i \in R_k$  do
22:        $w_k(i) \leftarrow \exp\left(-\frac{1}{2}(\mathbf{p}_i - \mu_k)^\top \Sigma_k^{-1}(\mathbf{p}_i - \mu_k) - \frac{\|\mathbf{c}_i - \mathbf{v}_k\|^2}{2\sigma_k^2}\right)$ 
23:     end for
24:      $w_{sum} \leftarrow \sum_{i \in R_k} w_k(i)$ 
25:     for all  $i \in R_k$  do
26:        $w_k(i) \leftarrow w_k(i)/w_{sum}$ 
27:     end for
28:   end for
29:   // Normalize per pixel
30:   for all  $i$  do
31:     for all  $k$  with  $i \in R_k$  do
32:        $\gamma_k(i) \leftarrow w_k(i)/\sum_n w_n(i)$ 
33:     end for
34:   end for
35: end procedure

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// Maximization step
34: procedure M-STEP
35:   for all  $k$  do
36:      $w_{sum} \leftarrow \sum_i \gamma_k(i)$ 
37:      $\Sigma_k \leftarrow \frac{1}{w_{sum}} \sum_i \gamma_k(i) (\mathbf{p}_i - \boldsymbol{\mu}_k)(\mathbf{p}_i - \boldsymbol{\mu}_k)^\top$ 
38:      $\boldsymbol{\mu}_k \leftarrow \frac{1}{w_{sum}} \sum_i \gamma_k(i) \mathbf{p}_i$ 
39:      $\mathbf{v}_k \leftarrow \frac{1}{w_{sum}} \sum_i \gamma_k(i) \mathbf{c}_i$ 
40:   end for
41: end procedure

// Correction step
42: procedure C-STEP
    // Spatial constraints
43:   for all  $k$  do
44:      $\overline{\boldsymbol{\mu}}_k \leftarrow \frac{\sum_{n \in N_k^4} \boldsymbol{\mu}_n}{|N_k^4|}$ 
45:   end for
46:   for all  $k$  do
47:      $\boldsymbol{\mu}_k \leftarrow \text{clampBox}\left(\frac{1}{2} \boldsymbol{\mu}_k + \frac{1}{2} \overline{\boldsymbol{\mu}}_k, (x_k, y_k)^\top \pm \left(\frac{r_x}{4}, \frac{r_y}{4}\right)^\top\right)$ 
48:   end for

    // Constrain spatial variance
49:   for all  $k$  do
50:      $(U, S, V^*) \leftarrow \text{SVD}(\Sigma_k)$ 
51:      $S_{1,1} \leftarrow \text{clamp}(S_{1,1}, 0.05, 0.1)$ 
52:      $S_{2,2} \leftarrow \text{clamp}(S_{2,2}, 0.05, 0.1)$ 
53:      $\Sigma_k \leftarrow USV^*$ 
54:   end for

    // Shape constraints
55:   for all  $k$  do
56:     for all  $n \in N_k^8$  do
57:        $\mathbf{d} \leftarrow (x_n - x_k, y_n - y_k)^\top$ 
        // Directional variance
58:        $s \leftarrow \sum_{i \in R_k} \gamma_k(i) \max(0, (\mathbf{p}_i - \boldsymbol{\mu}_k)^\top \mathbf{d})^2$ 
        // Edge strength
59:        $f \leftarrow \sum_{i \in R_k} \gamma_k(i) \gamma_n(i)$ 
        // Edge orientation
60:        $\mathbf{o} \leftarrow \sum_{i \in R_k} \nabla \frac{\gamma_k(i)}{\gamma_k(i) + \gamma_n(i)}$ 
        // Check for dominant kernels and staircasing
61:       if  $s > 0.2r_x$  or ( $f < 0.08$  and  $\angle(\mathbf{d}, \mathbf{o}) > 25^\circ$ ) then
62:          $\sigma_k \leftarrow 1.1\sigma_k$ 
63:          $\sigma_n \leftarrow 1.1\sigma_n$ 
64:       end if
65:     end for
66:   end for
67: end procedure

```