Image Downscaling Based on Neugebauer Model

Zixu Zhang, Kohei Inoue*, Kenji Hara, Kiichi Urahama

Kyushu University, 4-9-1, Shiobaru, Minami-ku, Fukuoka 815-8540, Japan

*Corresponding Author: k-inoue@design.kyushu-u.ac.jp

Abstract

We propose a method for image downscaling based on Neugebauer model, which expresses an arbitrary color as a weighted combination of primary colors called the Neugebauer primaries, which are the vertex colors in RGB color cube. The primary colors are highly saturated and can produce higher contrast image contents than the other colors inside the color cube. We define a similarity measure for evaluating the closeness between an arbitrary color and the Neugebauer primaries, and utilize it as a weight value for the weighted averaging pixel fusion. Experimental results show that the proposed method can produce downscaled images having the similar colors to the Neugebauer primaries.

Keywords: image downscaling, Neugebauer model, image enhancement.

1. Introduction

Image downscaling is a kind of image resizing or scaling techniques, which include image enlargement⁽¹⁾, image interpolation⁽²⁾, image super resolution^{(3),(4)}, content-aware image resizing⁽⁵⁾, making low resolution pixel art from pictures of standard sizes or vector images⁽⁶⁾, and enlargement of pixel art⁽⁷⁾. Downscaling is necessary to view a high-resolution image on digital cameras, mobile devices and social networks.

Conventional methods such as nearest neighbor, bilinear and bicubic interpolations are content-invariant, and therefore, some details in original images may be smoothed out by downscaling procedures. To overcome this problem, Kopf et al. proposed a content-aware image downscaling method that adapts the shape of downscaling kernel, yielding sharper and more detailed downscaled results⁽⁸⁾. Oztireli and Gross⁽⁹⁾ proposed a method which optimizes the perceptual quality of the downscaled results with SSIM⁽¹⁰⁾.

In this paper, we propose an image downscaling

method which focuses on the Neugebauer primaries that have high saturation and can produce high contrast images. Compared to Kopf's method⁽⁸⁾ and Oztireli's method⁽⁹⁾, the proposed method is computationally efficient because the proposed method simply computes a weighted average without optimization procedures such as the expectation-maximization algorithm used by Kopf et al. Experimental results show that the proposed method produces downscaled images with similar colors to the Neugebauer primaries.

2. Proposed Method

2.1 Neugebauer Primaries

In RGB color space, Neugebauer primaries⁽¹¹⁾ are the following eight colors: red, green, blue, black, cyan, magenta, yellow and white, which are denoted in an RGB color space $[0,1]^3$ by $R = [1,0,0], G = [0,1,0], B = [0,0,1], K = [0,0,0], C = \neg R, M = \neg G, Y = \neg B, W = \neg K$, respectively, where $\neg$ denotes the logical complement, e.g., $\neg G = \neg[0,1,0] = [1,0,1]$.

Let $p = [r, g, b]$ be an arbitrary RGB color vector, where $0 \leq r \leq 1, 0 \leq g \leq 1, 0 \leq b \leq 1$. Then we have the following equation:

$$p = w_R R + w_G G + w_B B + w_K K + w_C C + w_M M + w_Y Y + w_W W \quad (1)$$

where $\{w_X | X \in S\}$ for $S = \{R, G, B, K, C, M, Y, W\}$ is a set of the weights defined by

$$\begin{aligned} w_R &= r(1-g)(1-b), & w_C &= (1-r)gb, \\ w_G &= (1-r)g(1-b), & w_M &= r(1-g)b, \\ w_B &= (1-r)(1-g)b, & w_Y &= rg(1-b), \\ w_K &= (1-r)(1-g)(1-b), & w_W &= rgb. \end{aligned} \quad (2)$$

2.2 Similarity to the Neugebauer Primaries

The above weights $\{w_X | X \in S\}$ satisfy $w_X \geq 0$ for all $X \in S$, and $\sum_{X \in S} w_X = 1$. Therefore, it can be seen that each w_X indicates the similarity between an arbitrary color p and a primary color $X \in S$. Based on this observation, we

define a similarity measure between a color p and the set of the Neugebauer primaries S as follows:

$$s(p, S) = \max_{X \in S} (w_X). \quad (3)$$

This similarity $s(p, S)$ satisfies the following inequalities:

$$s(p, S) \geq \frac{1}{8}, \quad (4)$$

$$s(p, S) \leq 1. \quad (5)$$

The equality in (4) is achieved when $p = [\frac{1}{2}, \frac{1}{2}, \frac{1}{2}]$ as

$$w_X = \frac{1}{2} \cdot \frac{1}{2} \cdot \frac{1}{2} = \frac{1}{8} \quad (6)$$

for all $X \in S$, and the equality in (5) is achieved when p is a primary color as follows. For example, if $p = R$, then, from (2), we have

$$w_R = 1 \cdot 1 \cdot 1 = 1, \quad (7)$$

$$w_X = 0 \text{ for } X \neq R, \quad (8)$$

and hence $s(p, S) = w_R = 1$. The similar equation holds for every primary color.

2.3 Integer Scaling Factors

Let $H = [h_{ij}]$ be a high resolution input image with m rows and n columns, where $h_{ij} = [r_{ij}^h, g_{ij}^h, b_{ij}^h]$ for $i = 1, \dots, m$ and $j = 1, \dots, n$ denotes the RGB color vector at the pixel position (i, j) in H , and let $D = [d_{kl}]$ be the downsampled output image of H , where $d_{kl} = [r_{kl}^d, g_{kl}^d, b_{kl}^d]$ for $k = 1, \dots, \tilde{m} < m$ and $l = 1, \dots, \tilde{n} < n$ denotes the RGB color vector at the pixel position (k, l) in D . We suppose that $\tilde{m}$ and $\tilde{n}$ are given by a user as well as H .

Suppose that $m = \tilde{m}q + \hat{r}, 0 \leq \hat{r} < \tilde{m}$, where q and $\hat{r}$ denote the quotient and remainder, respectively. If $\hat{r} = 0$, then the scaling factor in the vertical direction is just q :

$$\tilde{m} = \frac{1}{q} \cdot m. \quad (9)$$

If $\hat{r} > 0$, then we upscale the vertical direction of H with the scaling factor $\tilde{m}(q+1)/m$ by Lanczos interpolation with size parameter 2, and downscale the upscaled image with the scaling factor $(q+1)$:

$$\tilde{m} = \frac{1}{q+1} \cdot \frac{\tilde{m}(q+1)}{m} \cdot m. \quad (10)$$

The horizontal direction is also scaled in the similar manner to the vertical direction described above. To preserve the aspect ratio of a given image, we will use a common q to both the vertical and horizontal directions.

2.4 Image Downscaling by Weighted Averaging

In this subsection, we suppose that $m = \tilde{m}q$ and $n =$

Fig. 1. Original images.

Fig. 2. Image downscaling results by the proposed method: $\alpha = 0.1, 1, 2, 10$ from top to bottom, and the image sizes are $200 \times 150, 100 \times 75, 40 \times 30, 16 \times 12$ from left to right.

$\tilde{n}q$ for simple notation. Then a pixel (k, l) in D corresponds to a $q \times q$ block in H , and a local indices (i_0, j_0) in a (k, l) block corresponds to the global indices (i, j) in H by $i = q(k-1) + i_0$ for $i_0 = 1, \dots, q$ and $j = q(l-1) + j_0$ for $j_0 = 1, \dots, q$. In this situation, the image downscaling procedure from H to D can be viewed as a transformation of a $q \times q$ block in H into a pixel in D . We formulate this transformation as a pixel fusion procedure by a weighted averaging as follows:

$$d_{kl}(\alpha, q) = \frac{\sum_{i'=1}^q \sum_{j'=1}^q S_{q(k-1)+i', q(l-1)+j'}^\alpha h_{q(k-1)+i', q(l-1)+j'}}{\sum_{i'=1}^q \sum_{j'=1}^q S_{q(k-1)+i', q(l-1)+j'}^\alpha}, \quad (11)$$

where we used the abbreviation

Fig. 3. Similarity images corresponding to Fig. 2.

Fig. 4. Mean similarity vs. α .

$$s_{q(k-1)+i', q(l-1)+j'}^\alpha = [s(h_{q(k-1)+i', q(l-1)+j'}, S)]^\alpha, \quad (12)$$

and α denotes a parameter for controlling the effect of the weights; for $\alpha > 1$, the similarity is enhanced, and for $\alpha < 1$, it is suppressed, especially for $\alpha = 0$, (11) outputs a uniform average color in the block.

3. Experimental Results

We used the images in Fig. 1 for image downscaling experiments (These images are available on the Web: <https://graphics.ethz.ch/~cengizo/imageDownscaling.htm>). Fig. 2 shows the image downscaling results of Fig. 1(a) by

Fig. 5. The image downscaling results by conventional methods. The size of each image is 128×96 .

Fig. 6. Similarity images corresponding to Fig. 5.

the proposed method with $\alpha = 0.1, 1, 2, 10$ from top to bottom, and the image sizes are $200 \times 150, 100 \times 75, 40 \times 30, 16 \times 12$ pixels from left to right. Fig. 3 shows grayscale images in which each pixel value denotes the similarity value of the corresponding pixel in Fig. 2. This figure shows that the downsampled images with larger value of α have larger similarity values in each resolution, that is also confirmed in the next figure, where we calculate the mean similarity value defined by

$$\bar{s}(\alpha, q) = \frac{1}{\tilde{m}\tilde{n}} \sum_{k=1}^{\tilde{m}} \sum_{l=1}^{\tilde{n}} s(d_{kl}(\alpha, q), S), \quad (13)$$

and show them in Fig. 4, where the vertical axis denotes $\bar{s}$, and the horizontal axis denotes α . The red, green, blue and cyan lines denote $q = 2, 4, 10, 25$, respectively. For all tested values of q , $\bar{s}$ increases monotonically with α .

Fig. 5 shows the image downscaling results by the related methods. Figs. 5(a)-(d) show conventional

Fig. 7. Mean similarity comparison.

subsampling, bicubic, box, Lanczos methods, respectively. Figs. 5(e)-(h) show the results with bilateral kernel⁽¹²⁾, generalized sampling⁽¹³⁾, content-adaptive downscaling⁽⁸⁾ and perceptual downscaling⁽⁹⁾, respectively. Fig. 6 shows the similarity images calculated from the downsampled images in Fig. 5. Fig. 7 shows the mean similarity values $\bar{s}$ of 128×96 downsampled images by the compared methods. In Fig. 7, the vertical axis denotes $\bar{s}$, and the horizontal axis denotes the names of the compared methods: subsampling, bicubic, box, Lanczos, bilateral, generalized, content, perceptual and the proposed ($\alpha = 2$) methods from the left to right. Among the compared methods, the subsampling method obtained the largest value of $\bar{s}$, and the proposed method is better than the subsampling one.

Fig. 8 shows the downsampled images of the images in Figs. 1(b)-(d) from top to bottom, where the four columns from the left to right correspond to the generalized, content-aware, perceptual and proposed methods, respectively.

4. Conclusions

We proposed a method for downscaling images based on the Neugebauer model, where we defined a similarity measure between a color and the Neugebauer primaries.

Experimental results showed that the downsampled images by the proposed method had higher similarity values to the Neugebauer primaries than the compared methods.

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Fig. 8. Image downscaling results for Figs. 1(b)-(d). The size of the downsampled images are 128×96 , 96×128 , 77×128 from the top to bottom rows.

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