Image Coding Algorithm Using Luminance-Chrominance Correlation and Spatial Correlation

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Abstract

Most of conventional image coding algorithms have reduced spatial redundancies for compressing data. In our previous works, we have proposed a novel coding algorithm focused on luminance-chrominance (L-C) redundancies. This paper presents an improved coding algorithm by using both spatial correlation and L-C correlation in an opponent color space. First of all, an input color image is divided into a luminance component and two chromatic components in the opponent color space. The chromatic components are divided into regions, and each region is averaged for reducing spatial redundancies. In order to reduce the L-C redundancies, a ratio of chrominance to luminance, we call C/L component, was newly introduced. Finally the spatially averaged C/L components in each region and wavelet-coded luminance data are transmitted as compact code. The color image can be restored without degrading its sharpness by the multiplication of transmitted averaged C/L components to decoded luminance data. Moreover, the proposed coding algorithm has an option to optimize the C/L components in S-CIELAB visual space. This paper discusses the performances of proposed coding algorithm with experimental results for natural full color test images.

Introduction

With the recent spread of the internet and multimedia technologies, digital images play more and more important role in human visual communications. In order to reduce image data quantity, several image compression algorithms have been developed. Most of them, such as JPEG, make use of the spatial correlation. In natural images, a strong correlation can also be observed among tri-color signals. However, the conventional algorithms were not fully utilizing the color correlation.

In 1990, one of the authors proposed a coding algorithm based on RGB color correlation.[1] Recently, a human-based opponent color space S-CIELAB, which is a spatial extension to CIELAB, was proposed.[2,3] In this paper, we focused on the signal correlation among luminance and chromatic components (L-C) in the S-CIELAB space, and propose a novel coding algorithm. In our algorithm, the redundancies of color components will be reduced by calculating the ratio of chrominance to luminance (C/L) and chromatic components will be spatially averaged remarkably by subsampling based on visual characteristics. Here, the spatial redundancies will be optimized in order to minimize the distance between an original image and the restored image in the S-CIELAB metric.

In the following sections, we introduce the procedure of the proposed coding algorithm and experimental results will be shown.

Basic Coding Model with L-C Correlation

Outline of the Basic Model

The procedure of the proposed basic model of the image coding/decoding techniques is schematized in Fig. 1. First of all, an image represented by RGB color signal is converted into opponent color components *O1, O2, O3* in the S-CIELAB color space, which will be defined in the next subsection. The S-CIELAB space was proposed by Zhang et al.[2,3] as a spatial extension to CIELAB to account for how spatial pattern influences color appearance and color discrimination. The component *O1* means luminance component and both *O2* and *O3* mean chromatic components. The sensitivity of the eye to luminance detail is higher than that of chrominance detail by human visual system. Therefore, in our algorithm, the luminance component *O1* will be coded with the original resolution by wavelet transform coding. On the other hand, chromatic components *O2* and *O3* will be divided into regions, and each region is averaged for reducing spatial redundancies. Then, the spatially averaged ratio C/L is calculated and the ratios will be transmitted along with wavelet coefficients as compact code.

The decoding process is very simple. The spatially averaged C/L ratio are upsampled by an interpolation algorithm Then, the restored chromatic components can be obtained by multiplying the upsampled C/L ratios by decoded luminance components.

The detailed algorithm is explained in the following subsections.

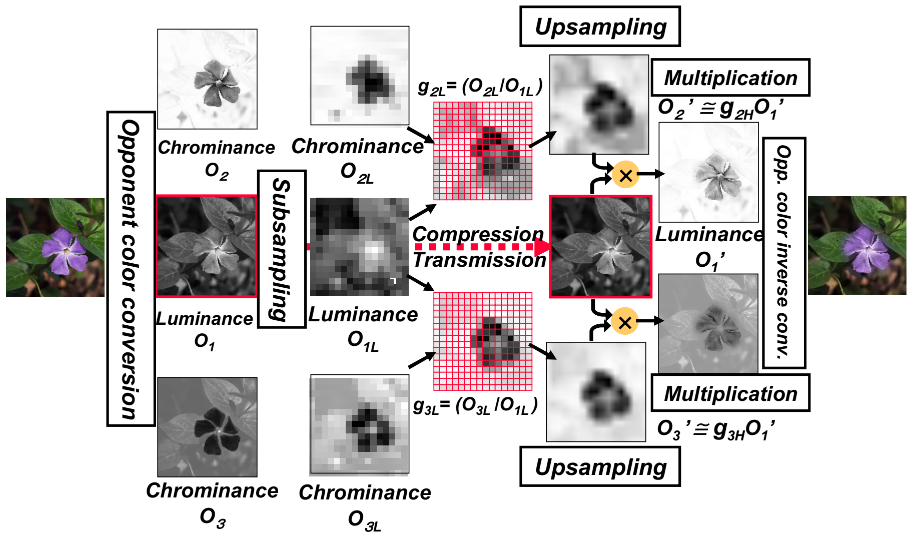


Figure 1. Process coding with Luminance-Chrominance correlation: Basic model

Color Conversion to an Opponent Color Space

In the S-CIELAB space, the color transformation converts the input image, specified in terms of the CIE 1931 XYZ tristimulus values, into three opponent colors planes that represent luminance *O1*, red-green *O2* and blue-yellow *O3* components. The linear transformation from XYZ to opponent colors is as follows:

$$\begin{bmatrix} O_1 \\ O_2 \\ O_3 \end{bmatrix} = \begin{bmatrix} 0.279 & 0.72 & -0.107 \\ -0.449 & 0.29 & -0.077 \\ 0.086 & 0.59 & -0.501 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \tag{1}$$

Coding and Decoding of Chromatic Components

In the object color region, such as people's skin, the green of a leaf and the red of a flower, strong correlation among luminance and chromatic components are observed. Since the sensitivity of the eye to chrominance detail is lower than luminance detail, the proposed algorithm reduces the resolution for *O2* and *O3* components remarkably by subsampling.

Let us consider opponent color components (O_1, O_2, O_3) for an image of XxY pixels. Let (O_{1L}, O_{2L}, O_{3L}) be spatially averaged components by subsampling for every KxK pixels. Then, the following C/L ratios (g_{2L}, g_{3L}) are transmitted instead of (O_2, O_3) components.

$$\begin{aligned} &g_{2L}(m,n) = O_{2L}(m,n) / O_{1L}(m,n) \\ &g_{3L}(m,n) = O_{3L}(m,n) / O_{1L}(m,n) \\ &m = 1,2,\cdots,M,\ n = 1,2,\cdots,N,\ \ M = [X/K],\ N = [Y/K] \end{aligned} \tag{2}$$

In the decoding stage, the spatially averaged C/L ratios (g_{2L}, g_{3L}) are upsampled by an interpolation algorithm.

$$\begin{aligned} &g_{2H}(x,y) = Interpolate\{g_{2L}(m,n), K\} \\ &g_{3H}(x,y) = Interpolate\{g_{3L}(m,n), K\} \\ &\qquad x = 1,2,\cdots,X,\ \ y = 1,2,\cdots,Y \end{aligned} \tag{3}$$

Then, the restored chromatic components $(\hat{O}_2, \hat{O}_3)$ can be obtained by multiplying the upsampled C/L ratio (g_{2H}, g_{3H}) by decoded luminance components $O_1^{'}$ as follows:

$$\begin{aligned} &\hat{O}_2(x,y) \cong O_1'(x,y) \cdot g_{2H}(x,y) \\ &\hat{O}_3(x,y) \cong O_1'(x,y) \cdot g_{3H}(x,y) \end{aligned} \tag{4}$$

Finally, the restored image can be obtained by converting $(O_1^{'}, \hat{O}_2, \hat{O}_3)$ into RGB color components.

Optimization of C/L Ratio Based on Visual Perception

In the proposed method, the color components are drastically compressed by using the spatial frequency characteristics in the S-CIELAB. So, the restored image should be verified in the S-CIELAB space. This section will modify the C/L ratio to optimize in the S-CIELAB. In the S-CIELAB model, each component (O_1, O_2, O_3) is perceived through two-dimensional separable spatial kernels (f^1, f^2, f^3) of the following formula, respectively.

$$O_j'(x,y) = O_j(x,y) \otimes f^j(x,y)\ \ ;\ \ j = 1,2,3,$$

$$\otimes : convolution$$

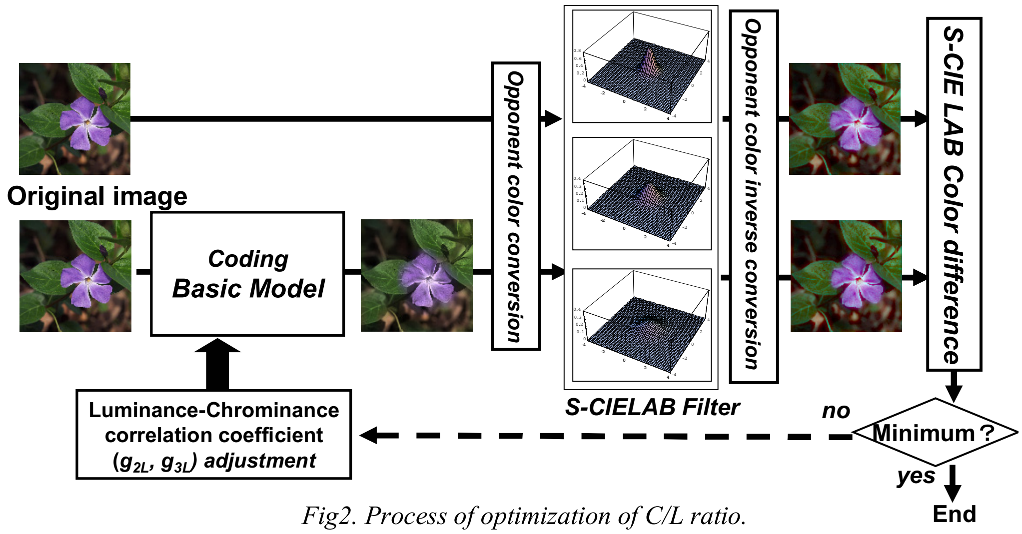


Fig2. Process of optimization of C/L ratio.

Figure 2. Process of optimization of C/L ratio.

$$f^{j}(x,y)=k^{j}\sum_{i} w_i^j E_i^j(x,y) \tag{5}$$

$$E_i^j(x,y)=k_i^j \exp\left(\frac{-(x^2+y^2)}{(\sigma_i^j)^2}\right) \tag{6}$$

The spatial kernel of each component is obtained by mixing two or three Gaussian distribution. Table 1 shows an example of parameters of kernels which are determined depending on viewing conditions. As shown in Table 1, the sensitivity of chromatic components becomes lower than luminance components remarkably.

In this model, the color difference between original components (O_2, O_3) and restored components $(\hat{O}_2, \hat{O}_3)$ is calculated throughout the spatial kernel, and the C/L components are optimized to minimize the difference. The model, we call S-CIELAB model, is schematized in Fig. 2.

Table 1. An Example of Parameters for S-CIELAB Kernels.

	w_i^j	σ_i^j
Luminance O_1 (*i=1~3*)	0.921 0.105 -0.108	0.0283 0.133 4.336
Red-Green O_2 (*i=1~2*)	0.531 0.330	0.0392 0.494
Blue-Yellow O_3 (*i=1~2*)	0.488 0.371	0.0536 0.386

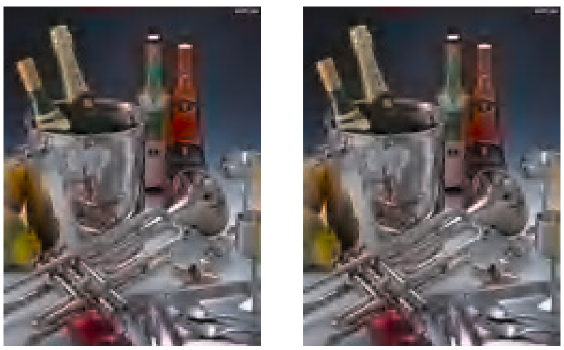
Experimental Result

Experiments for comparing with wavelet transform algorithm were performed on the viewpoints of color reproduction error and the compression rate using natural full color test images in SHIPP.

Figure 3 shows restored 'bottle' images with 4% and 6% compression ratio by the proposed basic model and the proposed S-CIELAB model. The image size is 120 x 160. Wavelet transform coding at the compression ratio 1/10 was commonly applied to the luminance components coding. The total compression ratio depends on the block size of subsampling. If 10 x 10 pixels are subsampled into one block region, the chromatic components are compressed into 1/100, respectively.

As shown in Fig. 3, effective results were obtained subjectively and the improvement of image quality can be confirmed by using S-CIELAB model. Especially, the color of red bottle was improved remarkably and the color of yellow fruits was not improved. The result shows that the error of *O2* components (red-green) was larger than *O3* components (yellow-blue), and it is in agreement with the vision characteristics. In our algorithm, the same subsampling ratio is used for both *O2* and *O3* components. In order to reflect vision model strictly, it is necessary to change the subsampling ratio by *O2* and *O3* components.

Compression rate 6% Compression rate 4%
(a) The proposed basic model.



Compression rate 6% Compression rate 4%
(b) The proposed S-CIELAB model.

Figure 3. Restored images.

Table 2. S-CIELAB Color Difference ΔE^*_{ab} Using the Proposed Basic Model and the S-CIELAB Model for Each Block Size.

Block size	K=4	K=5	K=10	K=20
Chrominance Compression ratio	1/16	1/25	1/100	1/400
Basic model	6.67	6.91	7.68	8.15
S-CIELAB model	6.62	6.88	7.72	8.01

Table 2 shows an objective evaluation by S-CIELAB color difference for the compression ratio. The S-CIELAB color difference ΔE^*_{ab} is calculated throughout spatial kernels and the difference reflects both spatial and color sensitivity. Therefore, the S-CIELAB color difference computed space-by-space while the conventional CIELAB color difference computed pixel-by-pixel. The image quality becomes high with increasing the compression ratio, because the influence with block distortion becomes small.

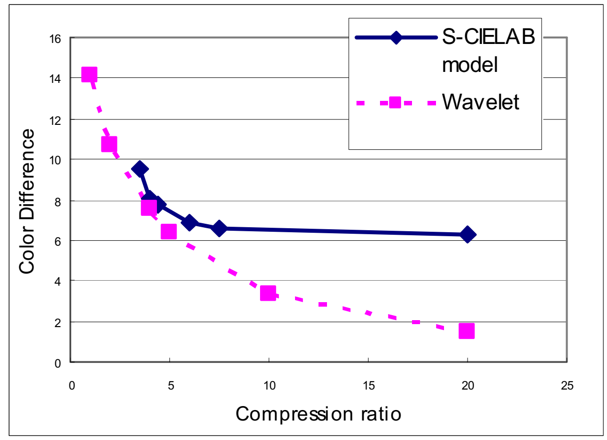


Figure 4. Relation between the compression ratio and S-CIELAB color difference ΔE^*_{ab}.

Figure 4 shows the S-CIELAB compression ratio vs. color difference for the proposed S-CIELAB model and the wavelet transform coding. In the case of compression ratio over 10%, the wavelet transform coding was a far good result from the proposed method. But, the color difference does not deteriorate so much for decreasing the compression ratio by using the proposed method. So, almost the same color difference was obtained at compression ratio around 5%. The same tendency was acquired also to other images. So, the proposed algorithm seems to work in high compression rate.

Consideration of the Algorithm Improvement

As mentioned above, the proposed model has an improving point for reflecting the difference of chrominance sensitivity between *O2* and *O3*. In order to solve the problem, the subsampling ratio must be changed by *O2* and *O3* components. Moreover, subsampling with the lattice block region still contains redundancy. The adjacent subsampled pixels may have the similar C/L ratio. Therefore, a dynamic subsampling should be adopted. For example, quad-tree can be applied to subsampling process instead of static block size subsampling. More complicated region segmentation may be effective for subsampling.

Conclusions

This paper proposed an image coding method by using both spatial correlation and luminance-chrominance correlation in an opponent color space. In our algorithm, opponent color components in S-CIELAB were used and the coding was optimized to minimize the S-CIELAB color difference. Experimental results showed that the proposed algorithm works effectively for high compression image coding.

As the future works, image quality should be improved by developing new subsampling algorithm.

References

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Biography

Toshiaki Fujisawa received his B.E. degree from Chiba University, Japan in 2003. Since 2003, he has been a graduate student in the Master's Program in Science and Technology of the same university. His current research interest is image coding based on vision model.