A Simple Image Coding by Projection of Principal Component in Segmented Color Areas

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Abstract

This paper proposes a simple color image coding method using Principal Component Analysis (PCA) in the segmented color areas. A color image is segmented in the CIELAB color space based on the human perception. In the clustered color area, the chroma a^* and b^* look to be strongly correlated with lightness L^*, and this tendency becomes remarkable by the segmentation. After the segmentation, each cluster is characterized by PCA. The segmented image is labeled with the class number. Since the class number is denoted by an integer value with narrow range but represents the segment color, it is compressed by the conventional loss-less coding. The coded class number is transmitted with the first Principal Component (PC) parameters. Because one set of PC parameters (eigen vector and centroid vector) is transmitted corresponding to each class, it takes small memory capacity. The chroma values of each pixel are approximately reproduced by the projection of first PC onto a*-b* plane along the first PC axis defined by eigen vectors. The first PC value on eigen vector axis mainly carries the lightness information with high resolution. It must be transmitted every pixel and compressed by the conventional Wavelet coding. After restoring the lightness L* from first PC, the full color image is reproduced by combining the estimated chroma components (a*, b*). This paper discusses the coding efficiency and the color reproduction error in relation to the segmented class number.

Introduction

With the spread of Internet and multimedia, digital image plays more and more important role in human visual communications. So far, a variety of image compression algorithms have been developed. Most of them, as represented by JPEG, make use of spatial correlations in 2D pixel array. Also a strong correlation is observed among tri-color signals in a local area of colored objects such as human face or green leaf.[1] However, the conventional compression method is not fully utilizing the color correlation. In the previous paper,[2-4] we proposed a simple image compression method by estimating the pixel color from the projection of lightness onto chrominance plane in the segmented PC space. This paper presents further improvements in our PC coding method using strong color correlations and discusses color reproducibility with compression rate. In the following sections, we introduce the segmentation procedure of clustered color area by k-means method, coding parameter extraction by PCA, and an experiment result is shown and compared.

Color Segmentation

The strong correlation in tri-color signals appears more clearly in the segmented object area with clustered color distributions. K-means algorithm is applied for the segmentation in CIELAB color space according to the following procedures.

[1] The initial color centers, what we call seed points, are placed at the suitable coordinates in the image color distributions.
[2] The Euclidian distance from each pixel point to a seed point is calculated and the pixel is temporary classified to the class of nearest seed point.
[3] The coordinates of the color centers in the segmented clusters are updated by recalculating the gravity center coordinates after classification.
[4] Procedures [2] and [3] are repeated until gravity centers stop to move and finally all the pixels are segmented into initially intended K classes

Through the above steps, the pixels located close each other in CIELAB color space are classified into the same cluster and the far pixels are classified into the different cluster.

The location of initial seed points is very important to get the better segmentation. Here the following processes are introduced to decide the position of seed points depending on the image color distributions

[1] The maximum and the minimum values in image color distributions on each axis of L*, a*, and b* are investigated.
[2] L*, a*, and b* axes are divided by constant step between the maximum and the minimum values and the temporary seed points are placed at the regular lattice points.
[3] The temporary seed points are rearranged in the higher order by counting the population of pixels distributed in the nearest neighborhood to the lattice points.

[4] The first K number of temporary seed points are chosen and assigned to the initial seed points used for K-means clustering algorithm.

In the experiment, the number of temporary seed points was set to 64 and the number of the initial seed points, that is, K was changed from 2 to 20.

Principal Component Analysis

In our compression algorithm, the chrominance components are approximated by the first PC based on the strong correlations between tri-color signals, where, PCA is applied to the data in each segmented cluster. PCA produces the new axes de-correlated each other and we can know which new axis has the maximum distribution in the clustered color pixels. Thus the most correlated colors in the same objects gather around the first PC. The first PC axis is a straight line to which the squared sum of distances from data points serves as the minimum.

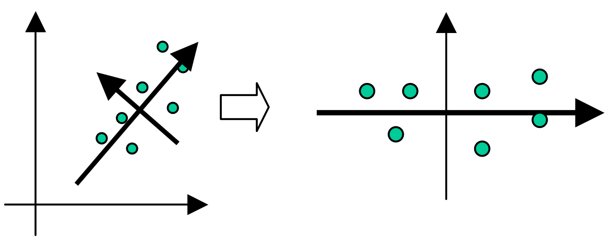

Figure 1. The de-correlated new axes by PCA

Calculation of PC is asking for the eigen value and eigen vector for the given covariance matrix ${}_k\Sigma_X$ of color vector s $\{{}_k\boldsymbol{X}\}$ in class k. An eigen vector expresses a new axis and the eigen value corresponds to the information power distribution on the axis.

A color vector ${}_k\boldsymbol{X}$ in class k is transformed into vector ${}_k\boldsymbol{Y}$ by Hotelling transform and projected onto PC space as

$$ {}_k\boldsymbol{Y} = {}_k\boldsymbol{A}({}_k\boldsymbol{X} - {}_k\boldsymbol{\mu}) \quad (1) $$

The matrix ${}_k\boldsymbol{A}$ is formed by the eigen vectors $\{{}_k\boldsymbol{e}_1, {}_k\boldsymbol{e}_2, {}_k\boldsymbol{e}_3\}$ of covariance matrix ${}_k\Sigma_X$ as

$$ {}_k\boldsymbol{A} = [{}_k\boldsymbol{e}_1, {}_k e_2, {}_k\boldsymbol{e}_3]^t \quad (2) $$

The covariance matrix ${}_k\Sigma_Y$ of $\{{}_k\mathbf{Y}\}$ is diagonalized in terms of ${}_k\mathbf{A}$ and ${}_k\Sigma_X$ whose elements are the eigen values of ${}_k\Sigma_X$ as

$$ {}_k\Sigma_Y = ({}_k\boldsymbol{A})({}_k\Sigma_X)({}_k\boldsymbol{A}^t) = \begin{bmatrix} {}_k\lambda_1 & 0 & 0 \\ 0 & {}_k\lambda_2 & 0 \\ 0 & 0 & {}_k\lambda_3 \end{bmatrix} \quad (3) $$

The eigen values ${}_k\lambda_1$, ${}_k\lambda_2$, ${}_k\lambda_3$ denote the variances which mean the energy distributed in principal axes.

Basic Chroma Compression Algorithm

The basic concept of our coding method lies in the prediction of chroma (a*, b*) components by the projection of lightness L* along the first PC axis onto the chrominance plane, where the strong correlation between Luma and Chroma components in the well segmented cluster makes this approximation possible. Since the lightness carries the most important information of image details with high resolution and gradations to human vision, it is transmitted every pixel compressed by conventional coding method. While, human vision is less sensitive to the chromatic information, then it is approximately predicted from the one set of parameters (class number, first eigen vector and mean vector) for each segmented cluster. The prediction of chroma components is performed as the followings.

- Using a class number, restore the first eigen vector and mean vector belonging to the class *k*.
- Estimate chroma by the projection of lightness L* onto a*-b* plane along the eigen vector linear line.

This situation is shown in Fig. 2. The 2-D chroma value of each pixel in the cluster is restored from the 1-D lightness location on the straight line of first eigen vector.

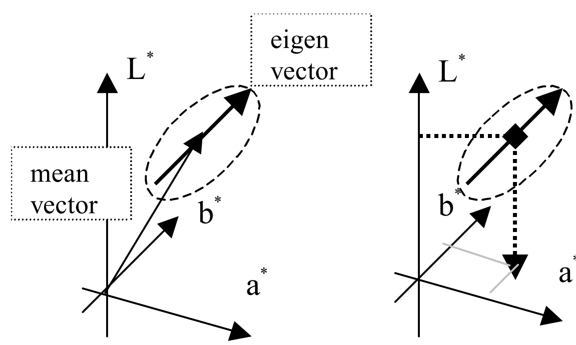

Figure 2. Prediction of chroma by the projection of L to a*-b**

In the basic model, the conventional ***Arithmetic coding*** is used for the compression of class number, and the ***Wavelet coding*** for the lightness L* image. The class number should be transmitted every pixel, but it was highly compressed by the arithmetic coding, because it has the same integer value with narrow range inside the segmented cluster. Since the eigen vector and mean vector need not to be transmitted for every pixel, but for each class up to maximum number of K, they are also well compressed.

However our basic model produces a large projection error under the specific condition that the eigen vector line is directed near parallel to the a*-b* plane. The small decoding error of L* value causes the large projection error for the the eigenvector line with slow slope as illustrated in Figure 3.

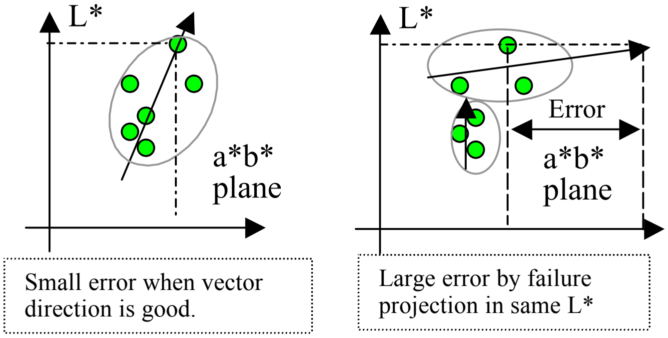

Figure 3. Chroma estimation error depending on eigen vector direction

Improved Chroma Compression Algorithm

The projection error in the basic model has reduced by the improved chroma estimation algorithm as follows

In the improved method, the 1-D pixel location coordinates $\{{}_kZ_p\}$ on the first *eigen vector axis* are saved instead of lightness L^*. The value ${}_kZ_p$ is calculated by

$$ {}_kZ_p = {}_ke_L({}_kp_L - {}_k\mu_L) + {}_ke_a({}_kp_a - {}_k\mu_a) + {}_ke_b({}_kp_b - {}_k\mu_b) \quad (4)$$

where, ${}_k\boldsymbol{e}_1 = [{}_ke_L, {}_ke_a, {}_ke_b]^t$, ${}_k\boldsymbol{p} = [{}_kp_L, {}_kp_a, {}_kp_b]^t$, and ${}_k\boldsymbol{\mu} = [{}_k\mu_L, {}_k\mu_a, {}_k\mu_b]^t$ denote the eigen vector, position coordinate of pixel p on 1st eigen vector axis, and mean vector for the 1st PC in class k, respectively. The coordinates $\{{}_kZ_p\}$ on the 1st eigen vector axis act like as just lightness information in the previous basic model. Because these coordinates have the positive and negative values, they are re-mapped to the normalized range of 0.0 ~ 1.0. Thus, $\{{}_kZ_p\}$ can be treated like as lightness information. Now we can estimate the chroma values more accurate than the basic model without extra error in the projection from L* to a*-b* plane, because the pixel coordinates $\{{}_kZ_p\}$ reflect the direct 1st PC values just laying on the 1st eigen vector axis itself.

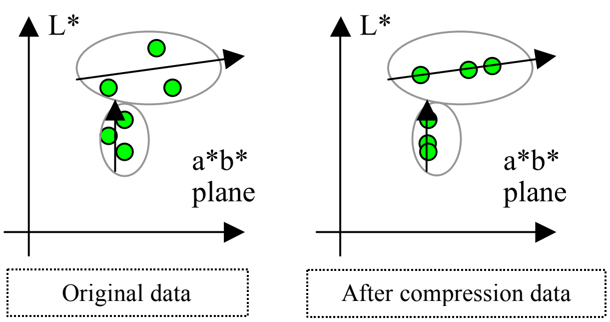

Figure 4. Prediction of chroma values using pixel coordinates on the 1st eigen vector axis

Experimental Result

The test images in SHIPP are used for the compression experiments. The performance of improved new algorithm is compared with that of basic model and also popular JPEG from the viewpoints of color reproduction error and the compression rate.

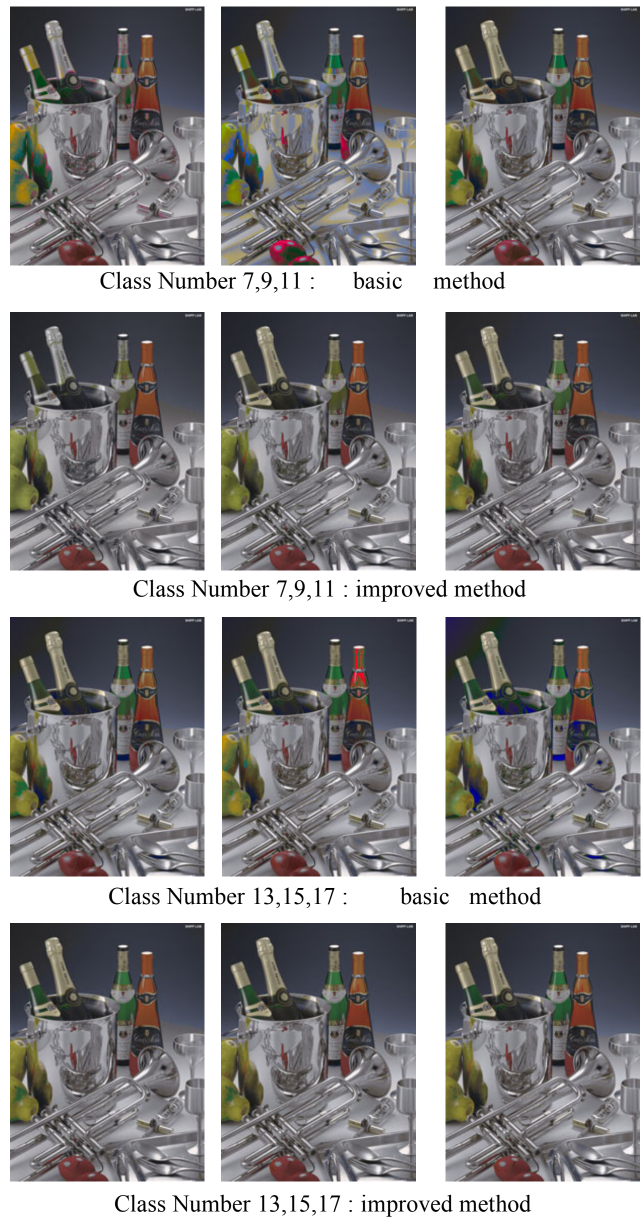

Figure 5. Comparison of the basic Chroma compression method and the Improve Chroma compression method.

Figure 5 shows the bottles images reproduced from the compressed codes by the proposed new algorithm in comparison with the previous basic model. Wavelet compression at the rate of 1/40 was commonly applied to compress the lightness in the basic model and the first PC coordinate of pixel in the new model. When the number of segmented classes is small, unnatural color reproduction errors appear in the basic model. As the segmented class number increases, the color errors decrease but the compression ratio goes to higher vice versa. As shown in Figure 5, the color reproduction quality in the proposed new model was clearly better than the previous basic model.

Figure 6 shows the changes in color difference ΔE^*_{ab} (rms) vs. class number between the proposed new model and the basic one. The color difference in the smaller number of classes dramatically reduced by the improved new algorithm. The color difference in new model approaches to the same order of 1/40 or 1/50 JPEG compression for K=10 or larger class number. Figure 6 tells us that the instability in color reproducibility observed for the previous basic model has been much improved by the new chroma compression algorithm. It turned out that the color error by the proposed new model roughly matches to that of 1/50 compression by JPEG at the class number K=11, and to that of 1/40 JPEG at K=20.

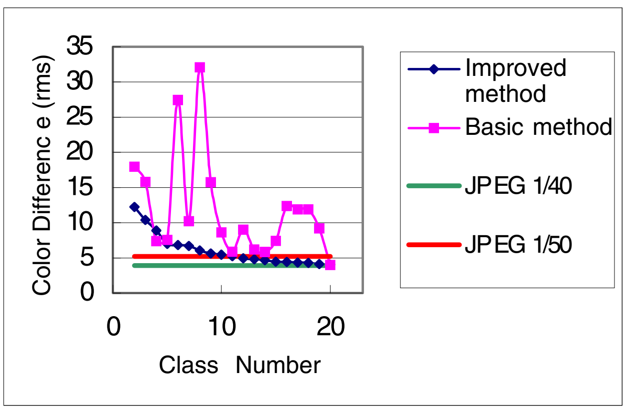

Figure 6. Relation between the number of classes and color difference

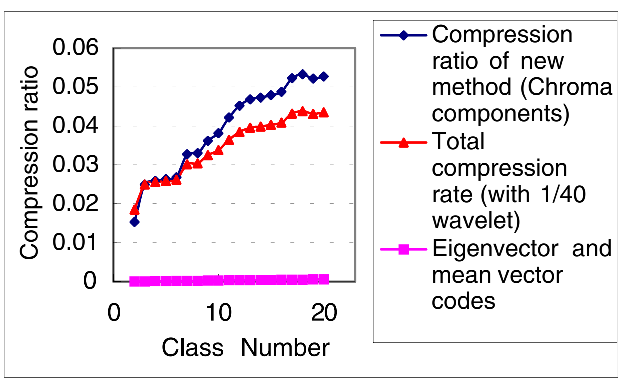

Figure 7. Compression rate for chroma components and total compression rate

Figure 7 shows the compression rate vs. class number for the proposed new method. The compression ratio is the same as the previous basic model. The compression ratio in total is still lower than JPEG or Wavelet coding at present.

The major reason lies in the insufficient compression ratio for the class number. Simply referencing to the compression ratio to get the same color difference, the proposed model takes about twice capacity as JPEG. However the image quality could not be determined by ΔE, but should be estimated through psychophysical opinion tests. Indeed, the proposed model resulted in the better rendition without unpleasant artifacts such as block noise in JPEG.

Conclusion and Future Works

The paper proposed a simple image compression method based on principal component coding paying our attention to the strong correlations between lightness and chroma in the segmented local area of the image. The improved new algorithm solved the instability in the prediction of chroma components by the previous basic model. Although the compression rate looks still worse as compared with JPEG, it reproduces better image rendition without artifacts such as block or mosquito noises. The proposed model has the advantage that can compress the tri-color channel simultaneously.

As the future works, further improvements in the color segmentation method and the introduction of lossy compression algorithm to the class number. Although the color clustering by K-means method classifies the nearest pixels to the same cluster based on the color distance, it would be more advantageous for a cluster to have extremely stretched distribution in the specific direction along the eigen vector. The key factor to get the higher compression rate mainly lies in the better coding algorithm for the class number. A new idea to combine the first PC coordinates with the class number is under planning.

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Biography

Koichi Sibasaki graduated from Department of Information and Image Science, Faculty of Engineering, Chiba University, Japan in 2002. He is a student at Graduate School of Science and Technology. His research interests include image segmentation, color image processing, and image compression.