Local MAP Estimation for Quality Improvement of Compressed Color Images

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Abstract

This paper concerns color image restoration aiming at objective quality improvement of compressed color images in general rather than merely artifact reduction. In compressed color images, colors are usually represented by luminance and chrominance components. Considering characteristics of human vision system, chrominance components are generally represented more coarsely than luminance component. To recover such chrominance components, we previously proposed a model-based chrominance restoration algorithm where color images are modeled by a Markov random field. This paper presents a color image restoration algorithm derived by the MAP estimation where all components are totally estimated. Experimental results show that the proposed restoration algorithm is more effective than the previous one.

Keywords: compressed color images, image restoration, MAP estimation, MRF, JPEG, JPEG2000

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1. Introduction

In transform-based image compression, transform coefficients are subjected to quantization, which produces information loss. The coarser the quantization, i.e., the higher the compression ratio, the larger the amount of information loss. At high compression ratios, the compressed images display noticeable artifacts. A well-known artifact is the blocking artifact in JPEG compression [1]. Many methods have already been proposed to remove artifacts, especially the blocking artifact.

According to [2], most postprocessing algorithms to reduce such coding artifacts are derived from two different viewpoints, i.e., image enhancement and image restoration. Image enhancement algorithms aim to improve subjective quality in image perception. Image enhancement is usually carried out by heuristic approaches, where no objective criterion is optimized. On the other hand, image restoration algorithms aim to estimate an original image given its compressed image. Several image restoration techniques have been proposed including projection onto convex sets (POCS) [3], total variation (TV) [4], and maximum a posteriori (MAP) estimation [5]. Most methods proposed so far have focused on artifact reduction for gray images. Several methods proposed for color images include [6] for color image enhancement and [7] for TV-based restoration. This paper concerns color image restoration aiming at objective quality improvement of compressed color images in general rather than merely artifact reduction.

In compressed color images, colors are usually represented by luminance and chrominance (YCbCr) components instead of red, green and blue (RGB) components. Then considering characteristics of human vision system, chrominance (CbCr) components are generally represented more coarsely than luminance component. For example, in JPEG compression, Cb and Cr components are usually downsampled by a factor of two at its compression stage, and afterward the downsampled chrominance components are interpolated at its decompression stage. Furthermore, at quantization step of discrete cosine transform (DCT) coefficients, DCT coefficients of chrominance components are generally quantized more coarsely than those of luminance components. To recover such chrominance components, we have already proposed a model-based method [8] where color images are modeled by a Markov random field (MRF) [9].

This paper presents a color image restoration algorithm where all components are totally estimated. The proposed algorithm is derived by the MAP estimation where two kinds of probability density functions (pdfs) are used: the pdf of errors between color components of an original image and those of its compressed image, and the pdf of color components of an original image. The independent and identically distributed (i.i.d.) Gaussian is used to model errors and an MRF is used to model original color images. The proposed algorithm can be considered as an extension of [5] for gray images to be able to apply to color images. However, we take a different approach considering that the method in [5] needs to set many parameters even for gray images and therefore its extension for color images may be very difficult for practical use. By our approach where the MAP estimation for a whole image can be approximately decomposed into pixelwise local MAP estimation, a very simple color restoration algorithm is derived.

2. Color Image Modeling by Markov random field

2.1. Markov random field

Let $\mathcal{L} = \{(i,j); 1 \le i \le N_1, 1 \le j \le N_2\}$ denote a finite set of sites of an $N_1 \times N_2$ rectangular lattice. Let $\eta_{ij}^X \subset \mathcal{L}$ denote the (i,j) pixel's neighborhood of a random field $X_{\mathcal{L}}$ [1] defined on $\mathcal{L}$. Let $\mathcal{C}_{ij}^X$ denote the set of cliques C associated with η_{ij}^X which contains the (i,j) pixel, i.e., $(i,j) \in \mathcal{C}_{ij}^X$. For example, in the first-order neighborhood, $\eta_{ij}^X = \{(i,j+1),(i,j-1),(i+1,j),(i-1,j)\}$ and $\mathcal{C}_{ij}^X = \{\{(i,j)\},\{(i,j),(i,j+1)\},\{(i,j),(i,j-1)\},\{(i,j),(i+1,j)\},\{(i,j),(i-1,j)\}\}$ which consists of one singleton and four doubleton cliques. Let the random field $X_{\mathcal{L}} = \{X_{ij}; (i,j) \in \mathcal{L}\}$ be a Markov random field (MRF) defined on $\mathcal{L}$ with X_{ij}s taking values from a common local state space Q_X. It is well known that an MRF is completely described by a Gibbs distribution

$$p(x_{\mathcal{L}}) = \frac{1}{Z_X} \exp\{-U(x_{\mathcal{L}})\}, \tag{1}$$

where $x_{\mathcal{L}}$ is a realization of $X_{\mathcal{L}}$ from the configuration space $\Omega_X = Q_X^{N_1 \times N_2}$ and

$$U(x_{\mathcal{L}}) = \sum_{(i,j)\in\mathcal{L}} \sum_{C \in \mathcal{C}_{ij}^X} U(x_C) \tag{2}$$

is the global energy function whereas $U(x_C)$ is the clique energy function and

$$Z_X = \sum_{x_{\mathcal{L}} \in \Omega_X} \exp\{-U(x_{\mathcal{L}})\} \tag{3}$$

is the partition function. For details on MRFs and related concepts such as the neighborhoods and cliques, see Ref. [9].

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[1] In this paper, x_A and $f(x_A)$ denote the set $\{x_{a_1}, \ldots, x_{a_l}\}$ and the multivariable function $f(x_{a_1}, \ldots, x_{a_l})$ respectively, where $A = \{a_1, \ldots, a_l\}$.

2.2. Color Image Model Using Gaussian MRF

A color image can be considered as a realization $\mathbf{x}_{\mathcal{L}} = \{\mathbf{x}_{ij}; (i,j) \in \mathcal{L}\}$ of a random field $\mathbf{X}_{\mathcal{L}} = \{\mathbf{X}_{ij}; (i,j) \in \mathcal{L}\}$. In YCbCr color space, $\mathbf{x}_{ij} = (y_{ij}^X, cb_{ij}^X, cr_{ij}^X)^T$, i.e., a color vector at (i,j) pixel is composed of a luminance component y_{ij}^X and two chrominance components cb_{ij}^X and cr_{ij}^X. Color images can be modeled by a Gaussian MRF (GMRF) characterized by the following local conditional pdf[2] :

$$
\begin{aligned}
p(\mathbf{x}_{ij} \mid \mathbf{x}_{\eta_{ij}^X}) &= \frac{1}{(2\pi)^{3/2}|\mathbf{\Sigma}_X|^{1/2}} \exp\{-\frac{1}{2}(\mathbf{x}_{ij} - \bar{\mathbf{x}}_{\eta_{ij}^X})^T(\mathbf{\Sigma}_X)^{-1}(\mathbf{x}_{ij} - \bar{\mathbf{x}}_{\eta_{ij}^X})\} \quad (4)\\
\bar{\mathbf{x}}_{\eta_{ij}^X} &= \frac{1}{|\mathcal{N}|}\sum_{\tau\in\mathcal{N}} \mathbf{x}_{ij+\tau}. \quad (5)
\end{aligned}
$$

Here $\bar{\mathbf{x}}_{\eta_{ij}^X}$ is the mean of neighboring pixels' color vectors $\mathbf{x}_{\eta_{ij}^X} = \{\mathbf{x}_{ij+\tau}, \tau \in \mathcal{N}\}$, where $\mathcal{N}$ denotes the neighborhood of $(0,0)$ pixel. For example, $\mathcal{N} = \{(0,1),(0,-1),(1,0),(-1,0)\}$ for the first-order neighborhood, and if $\tau = (0,1)$, $\mathbf{x}_{ij+\tau} = \mathbf{x}_{i,j+1}$. $\mathbf{\Sigma}_X$ is the covariance matrix of $\mathbf{x}_{ij} - \bar{\mathbf{x}}_{\eta_{ij}^X}$, i.e., $\mathbf{\Sigma}_X = E[(\mathbf{x}_{ij} - \bar{\mathbf{x}}_{\eta_{ij}^X})(\mathbf{x}_{ij} - \bar{\mathbf{x}}_{\eta_{ij}^X})^T]$, which is the expectation of $(\mathbf{x}_{ij} - \bar{\mathbf{x}}_{\eta_{ij}^X})(\mathbf{x}_{ij} - \bar{\mathbf{x}}_{\eta_{ij}^X})^T$.

3. Color Image Restoration

Let $\mathbf{x}_{\mathcal{L}} = \{\mathbf{x}_{ij}; (i,j) \in \mathcal{L}\}$ and $\mathbf{y}_{\mathcal{L}} = \{\mathbf{y}_{ij}; (i,j) \in \mathcal{L}\}$ denote an original color image and its compressed one, respectively. Given $\mathbf{y}_{\mathcal{L}}$, $\mathbf{x}_{\mathcal{L}}$ can be estimated by maximizing the a posteriori probability $p(\mathbf{x}_{\mathcal{L}} \mid \mathbf{y}_{\mathcal{L}})$, i.e., by MAP

[2] The used GMRF is one of the simplest GMRFs, which can model only nontextured smooth images. We here used this GMRF as a first step, though there are more complicated GMRFs applicable to textured images.

estimation. The MAP estimate $\hat{\mathbf{x}}_{\mathcal{L}}$ is written as

$$\hat{\mathbf{x}}_{\mathcal{L}} = \arg\max_{\mathbf{x}_{\mathcal{L}}} p(\mathbf{x}_{\mathcal{L}} \mid \mathbf{y}_{\mathcal{L}}), \tag{6}$$

where the a posteriori probability $p(\mathbf{x}_{\mathcal{L}} \mid \mathbf{y}_{\mathcal{L}})$ is described as

$$p(\mathbf{x}_{\mathcal{L}} \mid \mathbf{y}_{\mathcal{L}}) = \frac{p(\mathbf{y}_{\mathcal{L}} \mid \mathbf{x}_{\mathcal{L}})p(\mathbf{x}_{\mathcal{L}})}{\sum_{\mathbf{x}_{\mathcal{L}}} p(\mathbf{y}_{\mathcal{L}} \mid \mathbf{x}_{\mathcal{L}})p(\mathbf{x}_{\mathcal{L}})}. \tag{7}$$

Note that it is practically impossible to find the MAP estimate $\hat{\mathbf{x}}_{\mathcal{L}}$ since the search space over all possible configurations of $\mathbf{x}_{\mathcal{L}}$ is huge. To overcome this problem, hereinafter we consider mean-field-based decomposition of the a posteriori probability.

Assuming that the error vector at (i, j) pixel $\mathbf{e}_{ij}$ ($\mathbf{e}_{ij} = \mathbf{y}_{ij} - \mathbf{x}_{ij}$) introduced by lossy compression is modeled by i.i.d. Gaussian with zero-mean, $p(\mathbf{y}_{\mathcal{L}} \mid \mathbf{x}_{\mathcal{L}})$ is described as

$$p(\mathbf{y}_{\mathcal{L}} \mid \mathbf{x}_{\mathcal{L}}) = \prod_{(i,j)\in\mathcal{L}} p(\mathbf{y}_{ij} \mid \mathbf{x}_{ij}), \tag{8}$$

$$p(\mathbf{y}_{ij} \mid \mathbf{x}_{ij}) = \frac{1}{(2\pi)^{3/2}|\mathbf{\Sigma}_E|^{1/2}} \exp\{-\frac{1}{2}(\mathbf{y}_{ij} - \mathbf{x}_{ij})^T(\mathbf{\Sigma}_E)^{-1}(\mathbf{y}_{ij} - \mathbf{x}_{ij})\}, \tag{9}$$

where $\mathbf{\Sigma}_E$ is the covariance matrix of $\mathbf{e}_{ij}$, i.e., $\mathbf{\Sigma}_E = E[(\mathbf{y}_{ij} - \mathbf{x}_{ij})(\mathbf{y}_{ij} - \mathbf{x}_{ij})^T]$. Assuming an MRF for $\mathbf{x}_{\mathcal{L}}$ and then using the mean field approximation, $p(\mathbf{x}_{\mathcal{L}})$ can be decomposed as

$$p(\mathbf{x}_{\mathcal{L}}) \simeq \prod_{(i,j)\in\mathcal{L}} p(\mathbf{x}_{ij} \mid \langle\mathbf{x}\rangle_{\eta_{ij}^X}), \tag{10}$$

where $\langle\mathbf{x}\rangle_{\eta_{ij}^X}$ denotes the mean fields for $\mathbf{x}_{\eta_{ij}^X}$ [10]. Substituting (8) and (10) into (7) and replacing $\sum_{\mathbf{x}_{\mathcal{L}}}\prod_{(i,j)\in\mathcal{L}}$ by $\prod_{(i,j)\in\mathcal{L}}\sum_{\mathbf{x}_{ij}}$, we obtain the following decomposition for $p(\mathbf{x}_{\mathcal{L}} \mid \mathbf{y}_{\mathcal{L}})$ [10]:

$$p(\mathbf{x}_{\mathcal{L}} \mid \mathbf{y}_{\mathcal{L}}) \simeq \prod_{(i,j)\in\mathcal{L}} p(\mathbf{x}_{ij} \mid \mathbf{y}_{ij}, \langle\mathbf{x}\rangle_{\eta_{ij}^X}), \tag{11}$$

where

$$p(\mathbf{x}_{ij}\,|\,\mathbf{y}_{ij},\langle\mathbf{x}\rangle_{\eta_{ij}^X}) \quad = \quad \frac{p(\mathbf{y}_{ij}\mid\mathbf{x}_{ij})p(\mathbf{x}_{ij}\mid\langle\mathbf{x}\rangle_{\eta_{ij}^X})}{\sum_{\mathbf{x}_{ij}} p(\mathbf{y}_{ij}\mid\mathbf{x}_{ij})p(\mathbf{x}_{ij}\mid\langle\mathbf{x}\rangle_{\eta_{ij}^X})}. \tag{12}$$

In the following, $\mathbf{x}_{\eta_{ij}^X}$ is simply used for $\langle\mathbf{x}\rangle_{\eta_{ij}^X}$. Then $p(\mathbf{x}_{ij}\mid\mathbf{y}_{ij},\mathbf{x}_{\eta_{ij}^X}) = p(\mathbf{x}_{ij}\mid\mathbf{y}_{ij},\langle\mathbf{x}\rangle_{\eta_{ij}^X})$ is considered as local a posteriori probability (LAP). Using these LAPs, the global MAP estimation problem shown by Eq. (6) is approximately decomposed into the local MAP estimation problems

$$\hat{\mathbf{x}}_{ij} = \arg\max_{\mathbf{x}_{ij}} p(\mathbf{x}_{ij}\mid\mathbf{y}_{ij},\mathbf{x}_{\eta_{ij}^X}). \tag{13}$$

Considering that the LAP $p(\mathbf{x}_{ij}\mid\mathbf{y}_{ij},\mathbf{x}_{\eta_{ij}^X})$ is proportional to the product of two Gaussian pdfs for $p(\mathbf{y}_{ij}\mid\mathbf{x}_{ij})$ in (9) and $p(\mathbf{x}_{ij}\mid\mathbf{x}_{\eta_{ij}^X})$ in (4), the local MAP estimate $\hat{\mathbf{x}}_{ij}$ is explicitly derived as

$$\hat{\mathbf{x}}_{ij} = (\mathbf{\Sigma}_E^{-1}+\mathbf{\Sigma}_X^{-1})^{-1}(\mathbf{\Sigma}_E^{-1}\mathbf{y}_{ij}+\mathbf{\Sigma}_X^{-1}\bar{\mathbf{x}}_{\eta_{ij}^X}). \tag{14}$$

In order to solve (14) for all (i,j) pixels, their neighboring color vectors $\mathbf{x}_{\eta_{ij}^X}$ should be given. Since such a problem as shown in (14) can be solved iteratively as is popular in numerical analysis, we rewrite Eq. (14) as

$$\mathbf{x}_{ij}^{(p+1)} = (\mathbf{\Sigma}_E^{-1}+\mathbf{\Sigma}_X^{-1})^{-1}(\mathbf{\Sigma}_E^{-1}\mathbf{y}_{ij}+\mathbf{\Sigma}_X^{-1}\bar{\mathbf{x}}_{\eta_{ij}^X}^{(p)}), \tag{15}$$

where p represents the pth iteration. Color components derived from a given compressed color image are used as initial values $\mathbf{x}_{ij}^{(0)}$s in this iterative estimation. If chrominance components are downsampled, interpolated chrominance components are used as their initial values.

4. Implementation Details

In the calculation of $\bar{\mathbf{x}}_{\eta_{ij}^X}$ in (5), we here used the third-order neighborhood[3]. The third-order neighborhood of (i,j) pixel η_{ij}^X is shown in Fig. 1. However, if at least one of three components in $\mathbf{x}_{ij+\tau}$ is far from the corresponding component in $\mathbf{x}_{ij}$, $\mathbf{x}_{ij+\tau}$ was excluded from the calculation. In the following experiments, the used condition for exclusion was $|x_{ij+\tau}^k - x_{ij}^k| > 20$ $(k = 1,2,3)$, where x_{ij}^k is the kth component of $\mathbf{x}_{ij}$, i.e., $x_{ij}^1 = y_{ij}^X$, $x_{ij}^2 = cb_{ij}^X$, $x_{ij}^3 = cr_{ij}^X$. This elimination of outliers is necessary to prevent harmful effects by pixels which belong to different regions beyond edges with different color features. Regarding the elimination of outliers, experimental results with and without elimination are shown in Table 1. This experiment is one by the proposed method corresponding to one shown in Table 4 in Section 5. The amount of quality improvement with outlier elimination is larger than that without outlier elimination. The elimination procedure considering all components is slightly better than that considering only the luminance component, but the difference of quality improvement between the two elimination procedures is very small. This is considered to indicate that nearby pixels having different luminance values are likely to have different chrominance values.

Furthermore, to prevent an excessive change by the iterative estimation in (15), the following intermediate value $(\mathbf{x}_{ij}^{(p+1)})'$ between successive estimates

[3] For the third-order neighborhood, $\mathcal{N} = \{(0,1),(0,-1),(1,0),(-1,0),(1,1),(-1,-1),(1,-1),(-1,1),(0,2),(0,-2),(2,0),(-2,0)\}$

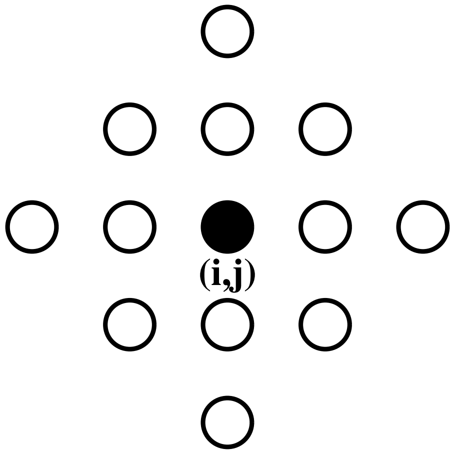

Figure 1: The third-order neighborhood of (i, j) pixel.

$\mathbf{x}_{ij}^{(p)}$ and $\mathbf{x}_{ij}^{(p+1)}$ was used instead of $\mathbf{x}_{ij}^{(p+1)}$:

$$(x_{ij}^{k(p+1)})' = w^k x_{ij}^{k(p+1)} + (1 - w^k) x_{ij}^{k(p)}, \tag{16}$$

where

$$w^k = \exp\{-\frac{|x_{ij}^{k(p+1)} - x_{ij}^{k(p)}|}{10}\}, k = 1, 2, 3. \tag{17}$$

Regarding this relaxation procedure, experimental results with and without relaxation are shown in Table 2. This experiment is one by the proposed method corresponding to one shown in Table 5 in Section 5. The relaxation procedure seems to be effective at higher quality compression levels, particularly for JPEG2000 images.

The proposed algorithm can be summarized for practical implementations as follows.

1 Set initial values $\mathbf{x}_{ij}^{(0)}$s at $p = 0$ to $\mathbf{y}_{ij}$s of a given compressed color image, i.e., $\mathbf{x}_{ij}^{(0)} = \mathbf{y}_{ij}$.

Table 1: Average image quality improvement in PSNR (dB) value by the proposed method with and without elimination of outliers for JPEG compressed images with chrominance downsampling. Two elimination procedures are used, one considering all components and the other considering only luminance component.

compression level	with elimination		without elimination
	all components	luminance component	
qf=50	0.58	0.58	0.46
qf=60	0.58	0.58	0.45
qf=70	0.60	0.59	0.46
qf=80	0.60	0.58	0.42
qf=90	0.56	0.54	0.31

2 Compute the mean of neighboring pixels' color vectors $\bar{\mathbf{x}}^{(p)}_{\eta^X_{ij}}$ considering the neighborhood η^X_{ij} shown in Fig. 1 and the above-mentioned elimination of outliers.

3 Compute the reestimate $\mathbf{x}^{(p+1)}_{ij}$ using (15).

4 Apply the relaxation procedure using (16) and (17).

In the following experiments, the iterative procedure in (15) was stopped at only one iteration because image quality in PSNR value sometimes decreases after the second iteration[4]. The covariance matrix $\mathbf{\Sigma}_X$ in (4) for each image was here computed using each original image, and the covariance ma-

[4]This might be a problem. To resolve it, we need to investigate convergence of our algorithm. It remains for future research.

Table 2: Average image quality improvement in PSNR (dB) value by the proposed method with and without relaxation procedure for JPEG and JPEG2000 compressed images without chrominance downsampling.

	compression level	with relaxation	without relaxation
JPEG	qf=50	0.92	1.03
	qf=60	0.93	0.98
	qf=70	0.98	1.01
	qf=80	1.00	0.96
	qf=90	1.02	0.96
JPEG2000	0.25bpp	0.20	0.23
	0.5bpp	0.28	0.23
	1.0bpp	0.31	0.14
	1.5bpp	0.19	-0.02
	2.0bpp	0.15	-0.04

trix $\mathbf{\Sigma}_E$ in (9) for each image was computed using each original image and its compressed one. Note that these matrices are global to the image and need to be transmitted/attached only once. Since covariance matrix is symmetric, the number of independent elements for each of these covariance matrices is six. Therefore the overhead for sending these parameters is $12 \times 4 = 48$ bytes in case of 4 byte allocation for each element. However in practice, the overhead can be reduced to 12 bytes since one byte integer is enough to represent each element as described in Section 5.

5. Experimental Results

Experiments were carried out using four standard color images (Lena, Milkdrop, Peppers, Mandrill), which are shown in Fig. 2. These images are 256×256 pixels in size and 24 bit per pixel (bpp) full color images. The proposed restoration algorithm was applied to JPEG compressed color images and JPEG2000 compressed ones. Our previous algorithm [8] and a PDE-based one (TV-based one) [11] were also applied for performance comparison. The previous algorithm was derived by maximization of the pdf for color image without changing luminance components in the color image. Its implementation details here are different from those in [8], and are similar to those for the proposed one described in Section 4.

Table 3 shows experimental results for JPEG compressed color images with chrominance downsampling at quality factor (qf) 70 as its compression level. In the table, bpp value for each image means bit per pixel for each compressed image. The amount of quality improvement in PSNR by the PDE-based method is the smallest among the three methods. The proposed method achieved better improvement than the previous one. The amount of quality improvement for Mandrill is small as is expected. It is probably because the used GMRF can model only nontextured smooth images and cannot model textured ones like Mandrill.

Table 4 shows the average of quality improvement for the four images in PSNR value. Results are shown for JPEG compressed images with chrominance downsampling at five different compression levels, i.e., qf=50, 60, 70, 80, and 90. At all compression levels, the amount of quality improvement in PSNR by the PDE-based method is the smallest, and that by the proposed

Table 3: Image quality in PSNR (dB) value by several methods for JPEG compressed images with chrominance downsampling at qf=70.

	quality factor = 70				
image	bpp	JPEG	PDE	previous	proposed
Lena	1.28	32.10	32.37	32.59	32.76
Milkdrop	1.04	32.11	32.39	32.82	32.99
Peppers	1.41	31.50	31.73	31.95	32.11
Mandrill	2.07	26.63	26.74	26.79	26.86

method is larger than that by the previous one.

Table 4: Average image quality improvement in PSNR (dB) value by several methods for JPEG compressed images with chrominance downsampling.

compression level	PDE	previous	proposed
qf=50	0.23	0.40	0.58
qf=60	0.23	0.42	0.58
qf=70	0.22	0.45	0.60
qf=80	0.20	0.50	0.60
qf=90	0.13	0.49	0.56

Table 5 shows the average of quality improvement in PSNR for the four images. Results are shown for JPEG and JPEG2000 compressed color images without chrominance downsampling at five different compression levels. For all cases, the amount of average quality improvement by the proposed method is larger than that by the previous one. Comparing with the results in Table 4, it is shown that significant quality improvement is achieved for JPEG compressed images without chrominance downsampling. Results for JPEG2000 compressed images show that the proposed and the previous methods are effective even for JPEG2000 images though the amount of improvement is small.

Table 5: Average image quality improvement in PSNR (dB) value by the two methods for JPEG and JPEG2000 compressed images without chrominance downsampling.

	compression level	previous	proposed
JPEG	qf=50	0.62	0.92
	qf=60	0.64	0.93
	qf=70	0.70	0.98
	qf=80	0.75	1.00
	qf=90	0.75	1.02
JPEG2000	0.25bpp	0.11	0.20
	0.5bpp	0.18	0.28
	1.0bpp	0.24	0.31
	1.5bpp	0.14	0.19
	2.0bpp	0.02	0.15

Regarding the overhead for sending information on the covariance matrices $\mathbf{\Sigma}_X$ in (4) and $\mathbf{\Sigma}_E$ in (9), one byte integer representation is enough for each element of the matrices. For example, in experiments shown in Table 4, almost same results for the proposed method were obtained by using low precision elements represented by one byte integer (to be precise, only 0.001 to 0.002 reduction of average quality improvement in PSNR). Therefore the overhead can be considered to be only 12 bytes. Furthermore, without adding the information on the covariance matrices to each compressed image file, the use of averaged covariance matrices over many images might be possible. For example, results using the averaged covariance matrices over the four images stay within 0.02 to 0.03 reduction of average quality improvement in PSNR.

Quality improvement by the proposed method can be described also in bit rate reduction point of view. Fig. 3 shows experimental results for JPEG color images with chrominance downsampling, where PSNR values are plotted for five different compression levels: qf=50, 60, 70, 80, and 90, and the leftmost and the rightmost point of each line correspond to qf=50 and qf=90, respectively. The horizontal line corresponding to PSNR=34dB in Fig. 3 shows that quality improvement in PSNR corresponds to 0.2 to 0.4 bit reduction for Peppers, Lena and Milkdrop.

This paper concerns objective quality improvement of compressed color images in general rather than merely artifact reduction. However, we believe that artifacts can be generally reduced by the proposed method. Though artifact reduction is usually difficult to be perceived at high quality compression levels, it can be sometimes perceived at low quality compression levels. For example, Fig. 4, Fig. 5 and Fig. 6 show a closeup image of JPEG compressed Lena at qf=40, the restored closeup image by the previous method and that by the proposed method, respectively. It can be visually perceived by careful inspection that the blocking artifact in Fig. 4 is reduced by the previous method and the proposed method in this order. Though the difference of quality improvement in PSNR between the previous method and the proposed method is only 0.24dB, the difference of visual quality between the two restored images shown in Fig. 5 and Fig. 6 can be perceived. This may indicate that restoration of all components by the proposed method is more effective to reduce the blocking artifact than chrominance restoration by the previous method.

6. Conclusions

This paper presented a model-based color image restoration algorithm in order to improve objective quality of compressed color images by postprocessing of given compressed images. The proposed algorithm was derived by the MAP estimation where errors between an original image and its compressed image are modeled by i.i.d. Gaussian and an original image is modeled by a Gaussian MRF. Thanks to MRF modeling, the global MAP estimation problem for a whole image is decomposed into local MAP estimation problems for each pixel. The proposed restoration algorithm was compared with our previous algorithm where only chrominance components are estimated. Experimental results for JPEG and JPEG2000 images show that the proposed restoration algorithm is more effective than the previous one.

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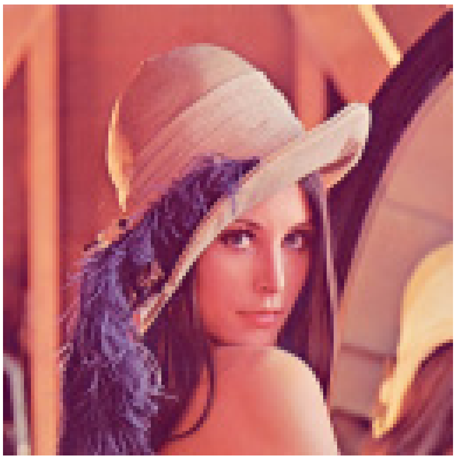
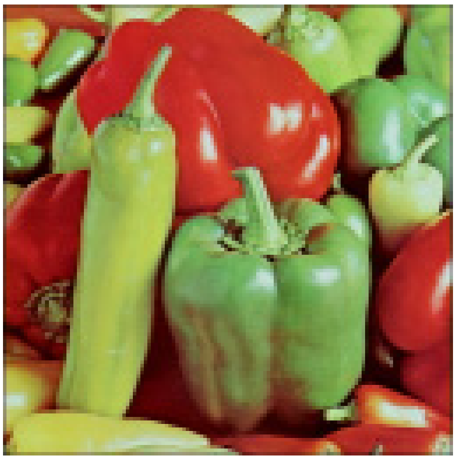
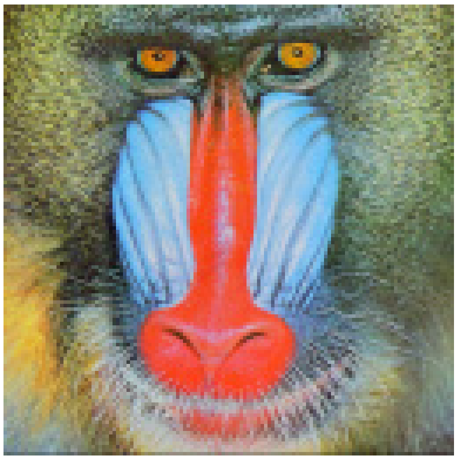



Lena Milkdrop

Peppers Mandrill

Figure 2: Four standard color images (Lena, Milkdrop, Peppers, Mandrill) used for experiments.

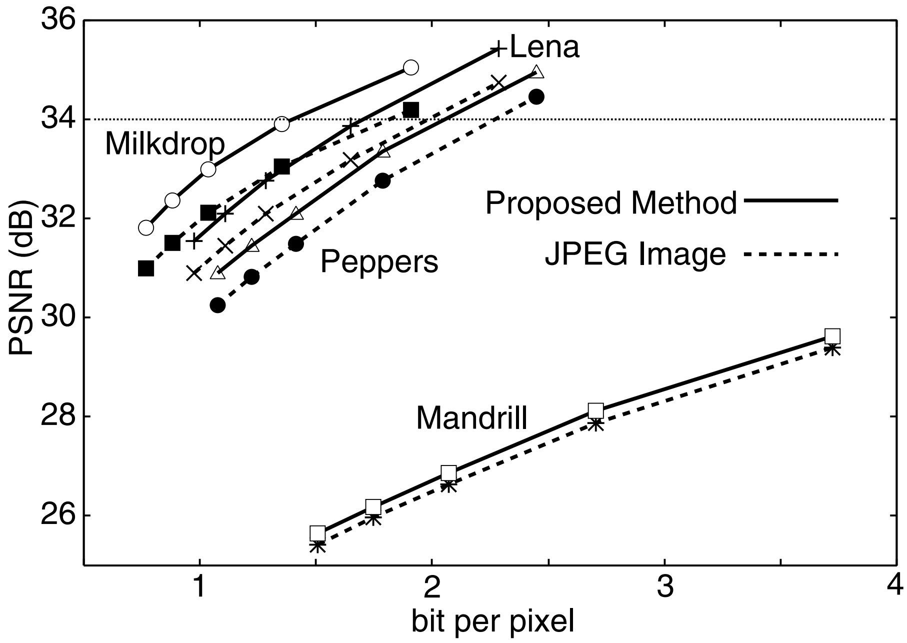


Figure 3: Experimental results for JPEG compressed four color images with chrominance downsampling. Performance is measured by PSNR.

Figure 4: JPEG compressed Lena with chrominance downsampling at qf=40 (PSNR=30.60dB).

Figure 5: Restored image by the previous method (PSNR=31.07dB).

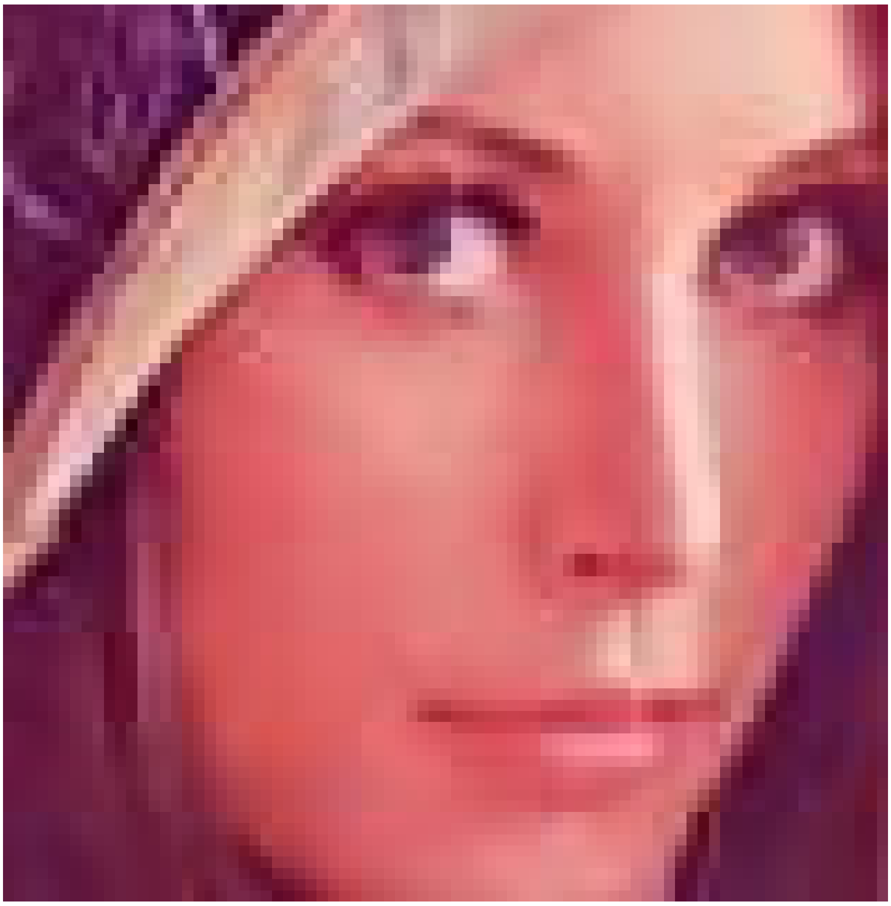


Figure 6: Restored image by the proposed method (PSNR=31.31dB).