QUALITY IMPROVEMENT OF COMPRESSED COLOR IMAGES USING A PROBABILISTIC APPROACH

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ABSTRACT

In compressed color images, colors are usually represented by luminance and chrominance (YCbCr) components. Considering characteristics of human vision system, chrominance (CbCr) components are generally represented more coarsely than luminance component. Aiming at possible recovery of chrominance components, we propose a model-based chrominance estimation algorithm where color images are modeled by a Markov random field (MRF). A simple MRF model is here used whose local conditional probability density function (pdf) for a color vector of a pixel is a Gaussian pdf depending on color vectors of its neighboring pixels. Chrominance components of a pixel are estimated by maximizing the conditional pdf given its luminance component and its neighboring color vectors. Experimental results show that the proposed chrominance estimation algorithm is effective for quality improvement of compressed color images such as JPEG and JPEG2000.

Keywords: compressed color image, chrominance estimation, MRF, JPEG, JPEG2000

1. INTRODUCTION

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 [1], 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.

For interpolation of downsampled chrominance components, several methods such as bi-linear interpolation and bi-cubic interpolation are usually used. However, such a conventional interpolation cannot recover high frequency components lost by downsampling and could cause color blurring in edges of a color image. To prevent such artifacts, Sugita et al. [2] proposed a chrominance interpolation method using information on luminance component which is not downsampled.

The interpolation aims to recover only resolution of chrominance components lost by downsampling. Alternatively, we aim to recover not only resolution lost by downsampling but also precision lost by a coarser quantization, if possible. Aiming at such recovery of chrominance components, we propose a model-based method where color images are modeled by a Markov random field (MRF). A simple MRF model is here used whose local conditional probability density function (pdf) for a color vector of a pixel is a Gaussian pdf depending on color vectors of its neighboring pixels. Chrominance components of a pixel are estimated by maximizing the conditional pdf given its luminance component and its neighboring color vectors. The estimation is carried out iteratively, and chrominance components derived from a given compressed color image are used as initial values for the iterative estimation. If chrominance components are downsampled, interpolated chrominance components are used as the initial values. The proposed chrominance estimation algorithm has a structure that chrominance components are estimated considering luminance component represented with higher resolution and precision, and therefore we can expect a better recovery of them.

The rest of this paper is organized as follows. In Section 2, after a brief review of MRF, a color image model used in this paper is described. In Section 3, the proposed chrominance estimation algorithm is described. Then after implementation details are given in Section 4, experimental results are given in Section 5. Conclusions are addressed in Section 6.

2. COLOR IMAGE MODELING BY MARKOV RANDOM FIELD

2.1 Markov Random Field

Let $\mathcal{L} = \{(i,j); 1 \leq i \leq N_1, 1 \leq j \leq N_2\}$ denote a finite set of sites of an $N_1 \times N_2$ rectangular lattice. Let $\eta_{ij} \subset \mathcal{L}$ denote the (i,j) pixel's neighborhood of a random field $X_{\mathcal{L}}$ [1] defined on $\mathcal{L}$. Let $\mathcal{C}_{ij}$ denote the set of cliques C associated with η_{ij} which contains the (i,j) pixel, i.e.,

[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 $A = \{a_1, \ldots, a_l\}$.

$(i,j) \in \mathcal{C}_{ij}$. For example, in the first-order neighborhood, $\eta_{ij} = \{(i,j+1),(i,j-1),(i+1,j),(i-1,j)\}$ and $\mathcal{C}_{ij} = \{\{(i,j)\},\{(i,j),(i,j+1)\},\{(i,j),(i,j-1)\},\{(i,j),(i+1,j)\},\{(i,j),(i-1,j)\}\}$ 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

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

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. [3].

2.2 A Color Image Model Using Gaussian MRF in YCbCr Space

Let $\mathbf{x}_{ij} = (y_{ij}, c_{ij}^b, c_{ij}^r)^T$ denote a color vector at (i,j) pixel in YCbCr space, where y_{ij} is a luminance component and c_{ij}^b and c_{ij}^r are two chrominance components. Let $\mathbf{c}_{ij} = (c_{ij}^b, c_{ij}^r)^T$ be a chrominance vector at (i,j) pixel. 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 $\mathbf{X}_{\mathcal{L}} = \{\mathbf{X}_{ij};(i,j) \in \mathcal{L}\}$, where $\mathbf{x}_{ij} = (y_{ij}, c_{ij}^b, c_{ij}^r)^T$. Color images are here assumed to be modeled by a Gaussian MRF (GMRF) characterized by the following local conditional pdf:

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

Here $\bar{\mathbf{x}}_{\eta_{ij}}$ is the mean of neighboring pixels' color vectors $\mathbf{x}_{\eta_{ij}} = \{\mathbf{x}_{ij+\tau}, \tau \in \mathcal{N}\}$, 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 $\tau = (0,1)$, $\mathbf{x}_{ij+\tau} = \mathbf{x}_{i,j+1}$. $\mathbf{\Sigma}$ is the covariance matrix of $\mathbf{x}_{ij} - \bar{\mathbf{x}}_{\eta_{ij}}$.

3. ESTIMATION OF CHROMINANCE COMPONENTS

A chrominance estimation algorithm derived in this section is the same as shown in [4]. However, it is here simply derived using Besag's pseudo-likelihood function [5]. Let $\mathbf{c}_{\mathcal{L}} = \{\mathbf{c}_{ij};(i,j) \in \mathcal{L}\}$ and $y_{\mathcal{L}} = \{y_{ij};(i,j) \in \mathcal{L}\}$ denote a chrominance image and a luminance image, respectively, and both images constitute a color image $\mathbf{x}_{\mathcal{L}}$. Our aim is to estimate a chrominance image while keeping a luminance image unchanged and the estimate $\hat{\mathbf{c}}_{\mathcal{L}}$ can be described as

$$\hat{\mathbf{c}}_{\mathcal{L}} = \arg\max_{\mathbf{c}_{\mathcal{L}}} p(\mathbf{x}_{\mathcal{L}}). \tag{6}$$

Note that it is practically impossible to find $\hat{\mathbf{c}}_{\mathcal{L}}$ since the search space over all possible configurations of $\mathbf{c}_{\mathcal{L}}$ is huge. To overcome this difficulty, we use the pseudo-likelihood function proposed by Besag [5] and approximate $p(\mathbf{x}_{\mathcal{L}})$ as

$$p(\mathbf{x}_{\mathcal{L}}) \simeq \prod_{(i,j)\in\mathcal{L}} p(\mathbf{x}_{ij} \mid \mathbf{x}_{\eta_{ij}}). \tag{7}$$

Using the local conditional pdf $p(\mathbf{x}_{ij} \mid \mathbf{x}_{\eta_{ij}})$, the chrominance vector $\mathbf{c}_{ij}$ in $\mathbf{x}_{ij}$ can be estimated as

$$\hat{\mathbf{c}}_{ij} = \arg\max_{\mathbf{c}_{ij}} p(\mathbf{x}_{ij} \mid \mathbf{x}_{\eta_{ij}}). \tag{8}$$

Note that only chrominance components are to be estimated since they are usually inferior to luminance component in quality.

The solution of (8) for the GMRF is explicitly described as follows. Let the covariance matrix in the GMRF shown in (4), $\mathbf{\Sigma} = \begin{pmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{pmatrix} = \begin{pmatrix} \sigma_y & \mathbf{\Sigma}_{yc} \\ \mathbf{\Sigma}_{cy} & \mathbf{\Sigma}_c \end{pmatrix}$, where $\sigma_y = \sigma_{11}$, $\mathbf{\Sigma}_c = \begin{pmatrix} \sigma_{22} & \sigma_{23} \\ \sigma_{32} & \sigma_{33} \end{pmatrix}$, and $\mathbf{\Sigma}_{yc} = (\sigma_{12}, \sigma_{13}) = \mathbf{\Sigma}_{cy}^T$. The GMRF $p(\mathbf{x}_{ij} \mid \mathbf{x}_{\eta_{ij}})$ in (4) can be decomposed as

$$\begin{aligned} p(\mathbf{x}_{ij} \mid \mathbf{x}_{\eta_{ij}}) &= p(y_{ij} \mid y_{\eta_{ij}}) p(\mathbf{c}_{ij} \mid y_{ij}, \mathbf{x}_{\eta_{ij}}), \quad (9) \\ p(y_{ij} \mid y_{\eta_{ij}}) &= \frac{1}{(2\pi)^{1/2}\sigma_y^{1/2}} \\ &\quad \cdot \exp\{-\frac{1}{2\sigma_y}(y_{ij} - \bar{y}_{\eta_{ij}})^2\}, \quad (10) \\ p(\mathbf{c}_{ij} \mid y_{ij}, \mathbf{x}_{\eta_{ij}}) &= \frac{1}{(2\pi)|\mathbf{\Sigma}_{c|y}|^{1/2}} \\ &\quad \cdot \exp\{-\frac{1}{2}(\mathbf{c}_{ij} - \mathbf{m}_{c|y})^T \mathbf{\Sigma}_{c|y}^{-1}(\mathbf{c}_{ij} - \mathbf{m}_{c|y})\}, \quad (11) \end{aligned}$$

where

$$\begin{aligned} \bar{y}_{\eta_{ij}} &= \frac{1}{|\mathcal{N}|}\sum_{\tau\in\mathcal{N}} y_{ij+\tau}, \quad (12) \\ \mathbf{m}_{c|y} &= \bar{\mathbf{c}}_{\eta_{ij}} + \mathbf{\Sigma}_{cy}\sigma_y^{-1}(y_{ij} - \bar{y}_{\eta_{ij}}), \quad (13) \\ \bar{\mathbf{c}}_{\eta_{ij}} &= \frac{1}{|\mathcal{N}|}\sum_{\tau\in\mathcal{N}} \mathbf{c}_{ij+\tau}, \quad (14) \\ \mathbf{\Sigma}_{c|y} &= \mathbf{\Sigma}_c - \mathbf{\Sigma}_{cy}\sigma_y^{-1}\mathbf{\Sigma}_{yc}. \quad (15) \end{aligned}$$

Considering that the maximum of (11) and then the maximum of (9) is derived at $\mathbf{c}_{ij} = \mathbf{m}_{c|y}$, the estimate of $\mathbf{c}_{ij}$, $\hat{\mathbf{c}}_{ij}$ in (8) is derived as

$$\hat{\mathbf{c}}_{ij} = \bar{\mathbf{c}}_{\eta_{ij}} + \mathbf{\Sigma}_{cy}\sigma_y^{-1}(y_{ij} - \bar{y}_{\eta_{ij}}). \tag{16}$$

Note that in order to obtain $\hat{\mathbf{c}}_{ij}$ for (i,j) pixel, its neighboring chrominance vectors $\mathbf{c}_{\eta_{ij}}$ should be given. Since such a problem can be solved iteratively as is popular in numerical analysis, we rewrite Eq. (16) as

$$\mathbf{c}_{ij}^{(p+1)} = \bar{\mathbf{c}}_{\eta_{ij}}^{(p)} + \mathbf{\Sigma}_{cy}\sigma_y^{-1}(y_{ij} - \bar{y}_{\eta_{ij}}), \qquad (17)$$

where

$$\bar{\mathbf{c}}_{\eta_{ij}}^{(p)} = \frac{1}{|\mathcal{N}|}\sum_{\tau\in\mathcal{N}} \mathbf{c}_{ij+\tau}^{(p)}, \qquad (18)$$

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

4. IMPLEMENTATION DETAILS

In the calculation of each component of $\bar{\mathbf{x}}_{\eta_{ij}}$ in (5), i.e., $\bar{y}_{\eta_{ij}}$ in (12) and $\bar{\mathbf{c}}_{\eta_{ij}}$ in (14), we here used the third-order neighborhood[2]. 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 conditions for exclusion were $|y_{ij+\tau} - y_{ij}| > 0.5s$ (s is the standard deviation of luminance values) for luminance component, or $|c_{ij+\tau}^b - c_{ij}^b| > 10$ or $|c_{ij+\tau}^r - c_{ij}^r| > 10$ for chrominance components.

Furthermore, to prevent an excessive change by the iterative estimation in (17), the following intermediate values $(\mathbf{c}_{ij}^{(p+1)})'$ between successive estimates $\mathbf{c}_{ij}^{(p)}$ and $\mathbf{c}_{ij}^{(p+1)}$ were used instead of $\mathbf{c}_{ij}^{(p+1)}$:

$$(c_{ij}^{b(p+1)})' = w^b c_{ij}^{b(p+1)} + (1-w^b)c_{ij}^{b(p)}, \qquad (19)$$
$$(c_{ij}^{r(p+1)})' = w^r c_{ij}^{r(p+1)} + (1-w^r)c_{ij}^{r(p)}, \qquad (20)$$

where

$$w^b = \exp\{-\frac{|c_{ij}^{b(p+1)} - c_{ij}^{b(p)}|}{10}\}, \qquad (21)$$
$$w^r = \exp\{-\frac{|c_{ij}^{r(p+1)} - c_{ij}^{r(p)}|}{10}\}. \qquad (22)$$

In the following experiments, the iterative procedure in (17) was stopped at only one iteration. The covariance matrix $\mathbf{\Sigma}$ in (4) for each image was computed using each given compressed image.

5. EXPERIMENTAL RESULTS

Experiments were carried out using four standard color images (Lena, Milkdrop, Peppers, Mandrill). These images are 256×256 pixels in size and 24 bit per pixel (bpp) full color images. The proposed chrominance estimation algorithm was applied to JPEG compressed color images and JPEG2000 compressed ones.

Experimental results for JPEG compressed color images with and without chrominance downsampling are shown in Fig. 1 and Fig. 2, respectively. In these figures, PSNR values and CIELAB distances are plotted for four different quality factor (qf) images: qf=60, 70, 80, and 90, and the leftmost and the rightmost point of each line correspond to qf=60 and qf=90, respectively. Larger quality factor image has higher quality, i.e., larger PSNR value and smaller CIELAB distance with larger bit rate (larger file size). From Fig. 1 and Fig. 2, it is seen that the proposed chrominance estimation algorithm is effective to improve quality of JPEG color images compressed both with and without chrominance downsampling. Additionally, Table 1 and Table 2 show quality improvement in PSNR value for JPEG compressed images (quality factor=80) with and without chrominance downsampling, respectively. It is seen that quality improvement for JPEG compressed images without downsampling is more significant than for those with downsampling.

Table 1: PSNR values for JPEG compressed images (quality factor=80) with chrominance downsampling and those improved by the proposed method.

		PSNR(dB)	
image	bpp	JPEG	proposed
Lena	1.65	33.18	33.55
Milkdrop	1.35	33.06	33.48
Peppers	1.79	32.77	33.13
Mandrill	2.71	27.87	27.95

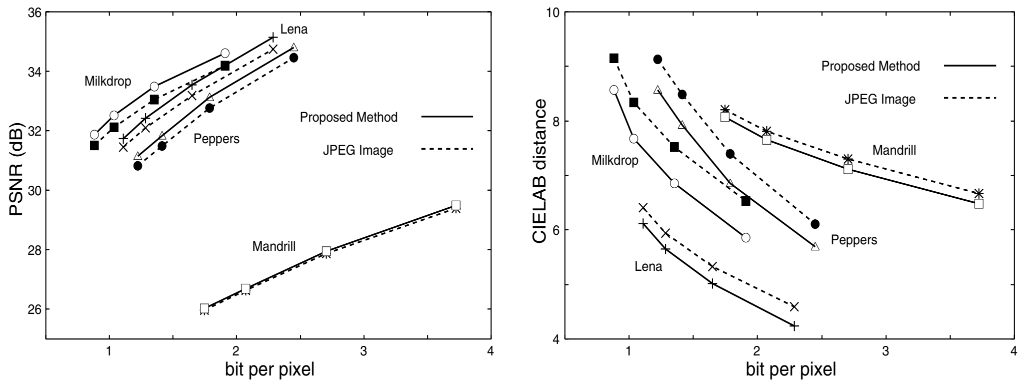
Table 2: PSNR values for JPEG compressed images (quality factor=80) without chrominance downsampling and those improved by the proposed method.

		PSNR(dB)	
image	bpp	JPEG	proposed
Lena	2.13	34.79	35.28
Milkdrop	1.83	36.31	37.11
Peppers	2.38	35.57	36.12
Mandrill	3.56	29.14	29.33

Table 3: PSNR values for JPEG2000 compressed images (bpp=1.0) without chrominance downsampling and those improved by the proposed method.

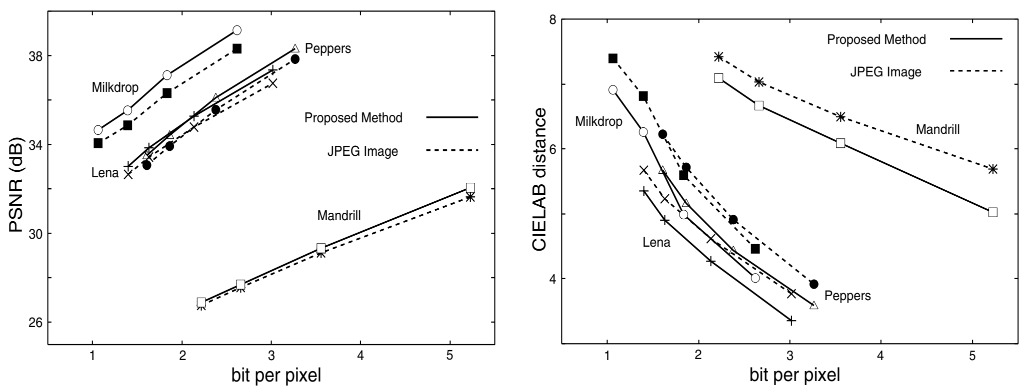
	PSNR(dB)	
image	JPEG2000	proposed
Lena	33.62	33.88
Milkdrop	36.49	36.74
Peppers	33.39	33.62
Mandrill	25.54	25.59

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



(a) (b)

Fig. 1: Experimental results for JPEG compressed four color images with chrominance downsampling. Performance is measured by (a) PSNR and (b) CIELAB distance.



(a) (b)

Fig. 2: Experimental results for JPEG compressed four color images without chrominance downsampling. Performance is measured by (a) PSNR and (b) CIELAB distance.

Experimental results for JPEG2000 compressed color images without chrominance downsampling are shown in Fig. 3. In this figure, PSNR values and CIELAB distances are plotted for five different bpp images: bpp=0.25, 0.5, 1.0, 1.5 and 2.0. Additionally, Table 3 shows quality improvement in PSNR value for JPEG2000 compressed images (bpp=1.0) without chrominance downsampling. It is seen that the proposed method is effective even for JPEG2000 compressed images.

6. CONCLUSIONS

This paper presented a model-based chrominance estimation algorithm in order to recover coarsely represented chrominance components in compressed color images. A simple MRF model was here used as a color image model, whose local conditional pdf for a color vector of a pixel is a Gaussian pdf depending on color vectors of its neighboring pixels. Chrominance components of a pixel were estimated by maximizing the conditional pdf given its luminance component and its neighboring color vectors. The estimation was carried out iteratively, and chrominance components derived from a given compressed color image were used as initial values for the iterative estimation. Experimental results show that the proposed chrominance estimation algorithm is effective to improve quality of JPEG color images compressed both with and without chrominance downsampling. Furthermore, it is shown that the proposed algorithm is effective even for JPEG2000 compressed color images.

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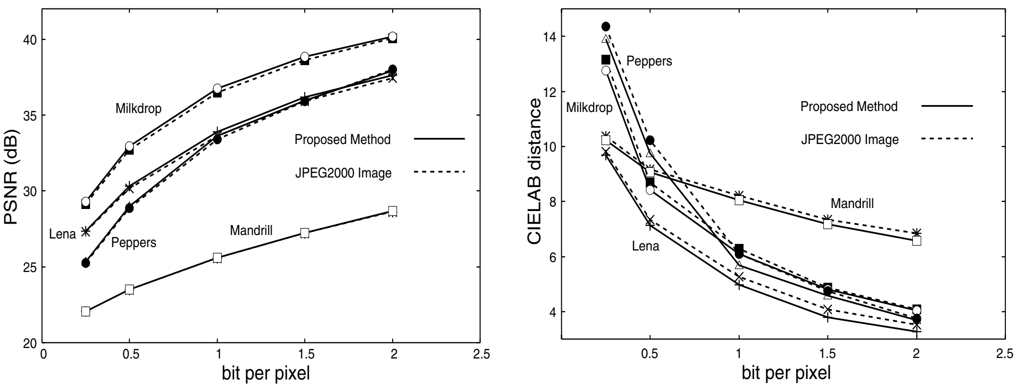

(a) (b)

Fig. 3: Experimental results for JPEG2000 compressed four color images without chrominance downsampling. Performance is measured by (a) PSNR and (b) CIELAB distance.

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