Adaptive quantization scheme for image compression based on human visual contrast sensitivity

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Abstract

We propose an adaptive quantization scheme for image compression based on human visual contrast sensitivity. The contrast sensitivity (CS) of different color attributes is measured by psychophysical experiments. The color dependent contrast sensitivity function (CSF) models including one lightness model, six chroma models and twelve hue models are established. According to the color attributes of each 8×8 sub-block of image, these models are used to calculate the corresponding CS. We use the CS of each sub-block to adaptively quantize the frequency spectrum coefficients of image. After adaptively quantizing, we set a threshold to make the high frequency coefficients zero to achieve image frequency domain compression. In order to evaluate the objective performance of the proposed scheme, peak signal-to-noise ratio (PSNR), universal image quality index (UQI), average structural similarity index (ASSIM), and visual information fidelity (VIF) of our scheme and other two methods are calculated. The psychophysical experiments with blurring, block and ringing artifacts as indicators are carried out to evaluate the visual quality of images compressed by different methods. The results show that the proposed scheme can effectively reduce the compression artifacts and improve the perceptual quality of images while maintaining the compression ratio.

1 Introduction

The JPEG compression algorithm proposed by Joint Photographic Experts Group is the most widely used in still image compression algorithm[1]. JPEG compression algorithm mainly includes five steps: color space transformation, image blocking, discrete cosine transform, quantization and coding. Quantization is the key to determine the compressed image quality[2]. After DCT transform, the high frequency coefficients can be made zero by quantization, which can obtain a high compression ratio. The JPEG standard provides an 8×8 fixed matrix as a quantization table. Although the quantization table considers the human visual charactoristics, different images use the same table during quantization, which cannot achieve the adaptative compression based on image color distribution. And it can lead to the deterioration of image visual quality, which is called compression artifacts, such as blurring, ringing and block artifacts[3]. Compression artifacts can be reduced by applying filters in the frequency domain[4–8]. These filtering operations usually cause serious blurring at the edges and details of the image. In order to improve the perceptual quality of compressed image, we propose an adaptive quantization scheme based on the contrast sensitivity (CS) characteristics of human visual system (HVS), which can improve the perceptual quality of compressed images while maintaining the compression ratio.

The contrast sensitivity function (CSF) is obtained by measuring the CS of grating patterns over a wide range of spatial frequencies. It plays an important role in image processing techniques based on perception. Many models for the CSF have been developed, for example: Mullen model[9], Barten model[10].

The CSF models have been widely used in quantization for image compression. In 2000, Nadenau established the luminance and chroma CSF models by experiments, and used the CSF models for image compression [3]. In 2013, Abu proposed a compression method using a psychovisual error threshold as quantization table for compression of gray images[11]. In 2014, the application of contrast sensitivity of HVS in video compression standards was studied[12]. In 2016, Yao used the DC coefficient of each sub-block and contrast sensitivity matrix calculated by CSF models to compress the image adaptively [13].

These studies used the fixed channel dependent CSF model, which cannot achieve the adaptive quantization according to the different color attributes of image.The HVS distinguishes colors by lightness(L), chroma(C) and hue(H) angle. Human eyes have different visual tolerances for L, C and H with different hue angles[14]. According to the color discrimination characteristics, we measure the CS of different L, C and H by psychophysical experiments. The color dependent CSF models including one lightness model, six chroma models and twelve hue models are established. We use the CS of each sub-block to adaptively quantize frequency spectrum coefficients of image. Our work provides an adaptive quantization scheme using the color dependent CSF models rather than the fixed tables in JPEG algorithm. The other compression process is the same as JPEG algorithm.

This paper structure is as follows. In Sec. 2 we measure the visual CS and establish the color dependent CSF models. In Sec. 3 we propose an adaptive quantization scheme based on the CS of each image sub-block. In Sec. 4, we give the objective and subjective performance comparison of this scheme with other compression methods, including JPEG[1] and Yao's[13]. Finally, we make a conclusion in Sec. 5.

2 The Establishment Of Color Dependent Csf Models

2.1 The measurement of color dependent CSF

We measure the color dependent CSF by using a cathode ray tube (CRT) monitor[15]. Fourteen observers which average age is 21 years participate in the psychophysical experiments. All observers are assessed to have normal or corrected to normal vision.

The test images are sine wave grating images extending in the horizontal direction. All test images are presented in the center of the screen with s size of 256×256 pixels, as shown in the Fig. 1. The spatial frequencies of the test images are varied from 0 to 20 cpd. The visual distance for observers is 2.02m, and the field of view is 2.1°×2.1°. Among the three color components L, C and H of test images, two components are constant, and the other component changes according to the sine wave. In L and C channels, we select 6 hue angle centers in the range of 0°-360° at 60° intervals. In H channel, we select 12 hue angle centers in the range of 0°-360° at 30° intervals.

The observers recognize the test images in the order of increasing spatial frequencies. They are required to select a test image that can just distinguish the sine wave fringes, the corresponding spatial frequency and the CS of the image should be recorded.

2.2 The Observer accuracy

In psychophysical experiments, it is necessary to analyze observer accuracy to evaluate the reliability of experimental data. In this paper, the standardized residual sum of squares(STRESS) is used to analyze the differences between observers[16]. STRESS is used to represent the consistency between the observed values of each group, which is generally expressed as a percentage. The higher the STRESS value, the worse the data consistency between different groups. The value of 0 indicates that the data of the two groups are completely consistent.

Table 1 shows the average STRESS values of all observer experimental data. As is shown in Table 1, the average STRESS values are distributed between 10–20, and the maximum value is 25.82. Compared with the same type visual observation experiments, the observer accuracy of the experiment in this paper is at the same level[17], which indicates that the observer experimental data obtained of our experiment are reliable.

Table 1
The average STRESS values of different test types.

Test type	Hue angle	STRESS	Test type	Hue angle	STRESS
Lightness	30°	14.91	**Hue**	15°	16.71
	90°	13.86		45°	13.98
	150°	12.64		75°	18.14
	210°	16.25		105°	18.62
	270°	9.25		135°	13.14
	330°	16.14		165°	13.63
Chroma	30°	23.08		195°	14.96
	90°	17.50		225°	20.38
	150°	19.69		255°	16.14
	210°	15.89		285°	18.96
	270°	25.82		315°	13.54
	330°	20.96		345°	18.81

2.3 The establishment of color dependent CSF models

For each spatial frequency, we calculate the average CS of all observers, which is the corresponding CS value at this spatial frequency. Figure 2 shows the relationship between CS values ($\log_{10}$ CS) and spatial frequencies at different hue angle centers.

In Fig. 2, the CS values of different hue angle centers vary widely in C and H channels. In Fig. 2(b), we can see that the CS values of yellow (90°) are significantly lower than other hue angle centers. In Fig. 2(c), the

CS values of red (15°) and blue-green (195°) are significantly lower than those of other hue angle centers. For different hue angle centers, the CS values in L channel are not significantly different, and the CS values in C and H channels vary widely.

According to the experimental results, we first establish a basic mathematical model in exponential form:

$$CS = a \times [\exp(-b \times f) - \exp(-c \times f)]$$

1

where the *a, b, c* are the fitting parameters, *f* is the spatial frequency.

We establish 19 color dependent CSF models according to the experimental results. In L channel, the CS values of six hue angle centers are averaged to establish one color dependent CSF model. In C and H channels, 6 and 12 color dependent CSF models are established respectively. Based on these color dependent CSF models, an adaptive quantization scheme is proposed in this paper.

3 Adaptive Quantization Scheme For Image Compression

3.1 The overview of adaptive quantization scheme.

The overview of the proposed scheme is shown in Fig. 3. An input RGB image is converted to LCH image, and the LCH image is divided into 8×8 sub-blocks. The DCT transform is processed on each sub-block. For each 8×8 sub-block, according to the probability of the color dependent CSF model corresponding to the pixel color, the CS of the sub-block is obtained by weighted summation. By using the corresponding CS and the spatial frequency distribution, the adaptive quantization matrix of each sub-block is calculated. The adaptive quantization matrix is used to quantize the DCT spectrum coefficients, and we finally realize the image frequency domain compression after thresholding. Using the compressed DCT frequency spectrum, the compressed RGB image is obtained by inverse DCT and color space conversion.

3.2 The calculation of adaptive quantization matrices

In order to obtain the chroma and hue adaptive quantization matrices of the sub-block, we propose a weighted summation method based on the pixel color probability. The specific steps are as follows:

Calculate the probability of each color dependent CSF model. We determine the corresponding color dependent CSF model according to the hue angle value of each pixel, and count the number of each color dependent CSF model in the sub-block. The probability P_i of each model is calculated by Eq. (2):

$$P_i = \frac{n_i}{64}$$

2

where i represents the index of the color dependent CSF model, in C channel, the i is 1 to 6, and in H channel, the i is 1 to 12. The n_i represents the number of the i-th color dependent CSF model, n_i ranges from 0 to 64.
Calculate the CS of each sub-block. We calculate the weighted CS by using the color dependent CSF model and corresponding probability. The CS of the sub-block is obtained by summing the weighted CS, which is calculated by Eq. (3):

$$CS = \sum_{i=1}^{i=m} P_i \times CS_i$$

3
where CS_i represents the CS of the i-th color dependent CSF model in each channel, and the m represents the number of color dependent CSF models in this channel.

Calculate adaptive quantization matrix of each sub-block. By substituting the spatial frequency distribution into the corresponding CS, we obtain the adaptive quantization matrix of the sub-block.
The frequency spectrum quantization of the sub-block is realized by multiplying the adaptive quantization matrix with DCT coefficients. For the quantized DCT coefficients, we set a threshold to make the coefficients below this threshold zero. The compressed DCT frequency spectrum is obtained. This paper does not encode the images when compressing them, the zero rate of the quantized DCT coefficients is used to represent the image compression ratio. After the inverse DCT and color space conversion, we can get the compressed RGB image.

4 Performance Comparison

4.1 Objective evaluation of compressed image quality.

In order to compare the objective performance of the proposed scheme with the existing compression methods, four evaluation indexes are calculated, including peak signal-to-noise ratio (PSNR)[18], universal image quality index (UQI)[19], average structural similarity index (ASSIM)[20] and visual information fidelity (VIF)[21]. PSNR is the common index used to assess the distortion of image[22]. The smaller the PSNR, the more serious the distortion of image quality. UQI measures the distortion caused by the loss of correlation, luminance and contrast. ASSIM compares the structural similarity between the original image and the compressed image. VIF evaluates the visual quality of the compressed image by quantizing the loss of image information in the distortion process. The maximum value of UQI, ASSIM and VIF is 1. The higher the value, the better the compressed image quality.

In order to compare the objective performance of different compression methods, 4 ISO standard images are compressed by using JPEG[1], Yao's[13]methods and the proposed scheme. The 4 images are named for Flowers, Bottles, Orchid and Bike. In order to achieve the same zero rate as JPEG and Yao's methods, the threshold is set to 7 when compressing images using the proposed scheme.

Figure 4 shows the original image, where the red rectangle marks the location of the clipping part. Two parts are selected for each image. Figure 5 shows the enlarged original and compressed images parts.

The proposed scheme shows a good advantage in the edge of image details. In Fig. 5, it can be seen that the compressed images obtained by the other two methods have serious ringing artifacts. Our scheme plays a good role in suppressing the ringing artifacts at the edge, which shows that at the same zero rate, our scheme has a good improvement on ringing artifacts. For the images compressed by the proposed scheme, the block artifacts are not obvious. These results verify that the proposed scheme has a good objective compression performance compared with other methods.

Table 2 shows the evaluation index values of different methods. It can be seen that the performance of our scheme is better than other methods at the same compression ratio, especially in the comparison with Yao's. For the UQI and VIF indexes, the proposed scheme is not as good as the JPEG algorithm in the "Flowers". For other images, our scheme has high index values.These results show that our scheme have a good objective compression performance at the same compression ratio.

Table 2
The objective performance comparison of different methods.

Image	Zero rate	Method	PSNR	UQI	ASSIM	VIF
Flowers	93%	Ours	**40.163**	0.636	**0.976**	0.869
		JPEG	39.864	**0.642**	0.973	**0.894**
		Yao's	39.333	0.572	0.962	0.747
Bottles	93%	Ours	**41.542**	**0.544**	**0.971**	**0.953**
		JPEG	39.595	0.522	0.948	0.938
		Yao's	39.740	0.505	0.909	0.819
Orchid	96%	Ours	**42.228**	**0.539**	**0.981**	**0.940**
		JPEG	41.087	0.510	0.969	0.931
		Yao's	40.409	0.446	0.921	0.802
Bike	91%	Ours	**40.019**	**0.747**	**0.945**	**0.938**
		JPEG	38.451	0.741	0.914	0.933
		Yao's	39.674	0.703	0.891	0.813

4.2 Subjective evaluation of compressed image quality

We carry out a psychophysical experiment to evaluate the visual quality of the images compressed by these methods. The experiment is carried out on a liquid crystal display (LCD) monitor. The resolution of the monitor is 86 dpi, and the display area of the test images is 140mm×188.5mm. The distance between observers and monitor is 40cm. The experiment is carried out in a dark room. 15 observers participate in the psychophysical experiment, and 4 test images (in Fig. 4) are evaluated.

As is shown in Fig. 6, the original and compressed images are displayed on the monitor. Observers are required to evaluate the blurring, ringing and block artifacts of the test images. Each image is evaluated according to five levels: excellent, good, fair, poor and bad[23]. The results are converted into numerical scores of 1 to 5. The score for an image is calculated by averaging all the scores of 15 observers. The subjective score results are shown in Table 3.

As is shown in Table 3, our scheme has good scores in three aspects: image blurring, ringing artifacts, and blockiness. It shows that at the same zero rate, our scheme can introduce less compression artifacts. Compared with the other two methods, some subjective evaluation scores of our scheme are more than 4, which indicates that the compressed image quality obtained by the proposed scheme can reach a good grade. The JPEG algorithm performs well in image blurring and blocking, but it has low scores in ringing artifacts, while Yao's method also shows a disadvantage in ringing artifacts. These results show our scheme can get a good visual quality of compressed images at the same compression ratio, which verifies the objective evaluation results in Section 4.1.

Table 3
Subjective evaluation scores of different methods.

Image		**Flowers**	**Bottles**	**Orchid**	**Bike**
Blurring	Ours	**3.94**	**4.26**	**4.20**	**4.02**
	JPEG	3.50	3.34	3.54	3.56
	Yao’s	2.10	2.17	2.20	2.44
Ringing artifacts	Ours	**4.00**	**4.17**	**3.92**	**4.11**
	JPEG	3.19	3.19	3.33	3.47
	Yao’s	1.68	1.68	1.60	2.20
Block artifacts	Ours	**4.40**	**4.44**	**4.05**	**4.00**
	JPEG	3.94	3.70	3.58	3.57
	Yao’s	2.09	2.38	1.76	2.10

5 Conclusion

This paper proposes an adaptive image quantization scheme based on human visual contrast sensitivity. We measure the visual CS and establish nineteen color dependent CSF models including one lightness model, six chroma models and twelve hue models. These models are used for the adaptive quantization of image frequency domain. For each 8×8 sub-block of the original image, the corresponding CS is obtained by summing the color dependent CS of all pixels in the sub-block. We use the CS of each sub-block to adaptively quantize the DCT spectrum coefficients of image, and finally realize the image frequency domain compression. In order to evaluate the performance of the proposed scheme objectively, the PSNR, UQI, ASSIM and VIF of our scheme and other two methods are calculated. We also carry out the psychophysical experiments to evaluate the visual quality of images compressed by different methods. These results show that the proposed scheme can effectively reduce compression artifacts and improve the perceptual quality of compressed images while maintaining the compression ratio.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Availability of data and materials Not applicable.

Competing interests The authors have no relevant financial or nonfinancial interests to disclose. And have no competing interests to declare that are relevant to the content of this article.

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Authors' contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Yongle Hu and Yusheng Lian. The first draft of the manuscript was written by Yongle Hu and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Figures

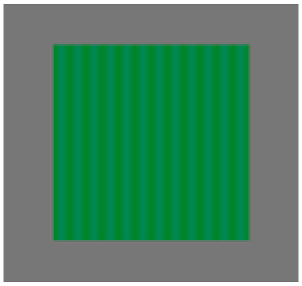

Figure 1

The test image of color dependent CSF.

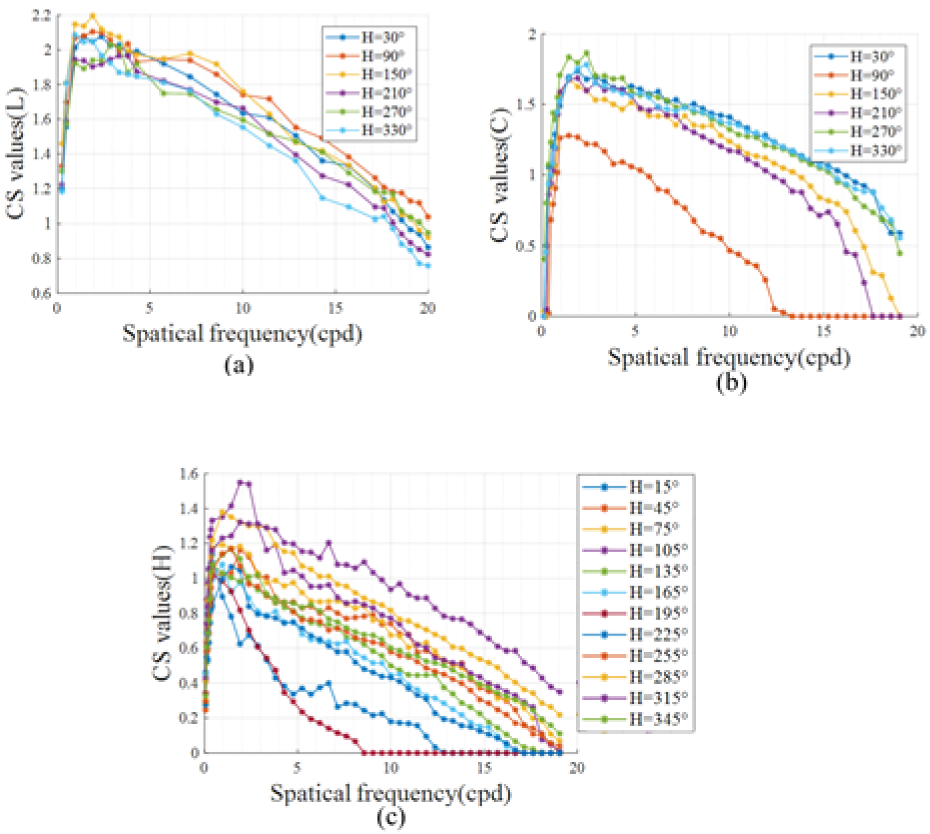

Figure 2

CS values at different hue angle centers:(a) lightness, (b) chroma, (c) hue.

Figure 3

The overview of the proposed scheme.

Figure 4

The original images.

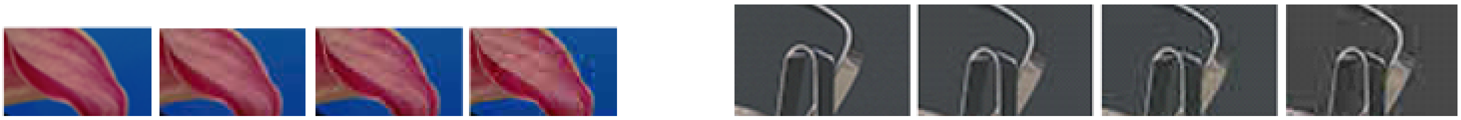

Figure 5

The original and compressed image parts(from left to right: original; ours; JPEG; Yao's).

Figure 6

The test images of subjective evaluation.