



A BLIND ASSESSMENT METHOD OF IMAGE COMPRESSION QUALITY BASED ON IMAGE VARIANCE

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Submitted: July 29, 2015

Accepted: Jan. 18, 2016

Published: Dec. 1, 2016

Abstract- The assessment of image compression result can not only evaluate the quality of image compression results and to a certain extent, can also find the advantages and drawbacks of various compression methods. At the same time, it can provide a reference for the compressed image restoration. Firstly, the classification and shortages of image quality assessment methods are presented. Then, several objective assessment methods usually used for image compression quality are introduced and the recent research progresses are shown. Finally, in view of the shortages of traditional image assessment methods and the existing blind assessment methods, based on image invariance, we propose a blind assessment method of image compression quality by considering the edge detail recovery and artifact removing. Compared with the traditional blind assessment methods, our method is simple in form and evaluation system is easily implemented. The experimental results also show that it is reasonable and effective.

Index terms: Image compression; quality assessment; objective assessment; blind assessment; image variance.

I. INTRODUCTION

Image quality assessment has a wide range of applications in the digital image and video processing, image transmission, video communications, medical, aviation, education, fingerprint and face recognition and other fields. It is also one of the important ways to evaluate various image and video processing system or algorithm [1-5]. The assessment of image compression results plays an important and indispensable role in image compression. It can evaluate not only the quality of image compression results and also the methods of image compression in a certain extent. For the same image or the same compression method, the results obtained by using different compression quality assessment methods may vary widely, even be opposite. Therefore, in order to effectively distinguish the efficiency and effectiveness among different compression methods and obtain better compression quality, the quality assessment of image compression results is very important and necessary to image compression.

The image compression quality assessment methods can be divided into objective assessment methods and subjective assessment methods. The subjective assessment method directly evaluates the image compression quality through eyes. Although the assessment results are consistent with human visual characteristics and relatively reliable, but the method has poor portability, test results are unstable and often vary with different individuals. So, in order to make the assessment results more accurate, a large number of persons must be included. The assessment process is not only complicated, but also time-consuming and arduous.

More importantly than all of that, the subjective method can not be applied to automatically obtain the assessment results. The objective assessment method gives the results based on a model or an algorithm. It makes up for the shortages of the subjective assessment method and is widely used to evaluate the image compression methods and the image compression quality. Now, it is the focus of the research about image compression quality assessment.

For objective assessment methods, mean square error (MSE) and peak signal to noise ratio (PSNR) based on simple error statistics are commonly used. Because of not considering the human eye vision features, their conclusions may be inconsistent with those obtained by subjective assessment methods. Therefore, the error statistics methods combined with the human visual characteristics (HVS) have been widely studied in recent years. Despite some researches show that the assessment methods based on HVS are superior to the simple statistics methods,

they have a common shortcoming, that is, the original image or reference image is required for assessment [6, 7]. In fact, in many practical applications, such an image is often unavailable. So, they still can't meet the needs of practical applications.

The image compression quality assessment method which doesn't depend on the original image or reference image is called blind assessment method. Although blind assessment method is studied less than those methods using reference images, it is still an important research direction in the future and has widely been paid attention because it does not depend on the reference image and can meet the needs of many practical applications.

In this paper, firstly, we present the classification and shortages of some traditional image quality assessment methods. Then, several objective assessment methods usually used for image compression quality are introduced and the recent research progresses are shown. Finally, in view of the shortages of traditional image assessment methods and the existing blind assessment methods, based on image invariance, we propose a blind assessment method of image compression quality considering the edge detail recovery and artifact removing. Compared with the traditional blind assessment methods, our method is simple in form and evaluation system is easily implemented. The experimental results also show that it is a kind of reasonable and effective method.

II. REDUNDANT FUZZY TRANSFORMATION METHOD FOR IMAGE COMPRESSION

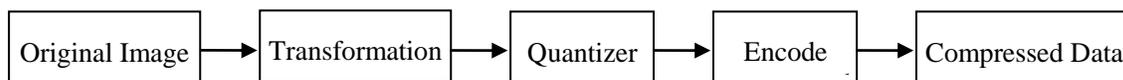
Two basic principles are usually used for the digital image compression. One is the correlation of digital image. Another is the visual psychological characteristics of human. There are very strong correlations among adjacent pixels of an image and between the corresponding pixels of the adjacent frames of moving images. In order to compress the digital image, we remove or reduce these correlations, namely remove or reduce the redundancy of image information. Therefore, how to remove redundant information of the image is the key to the image compression technology. The redundancy degree of image information determines the compression ratio in the process of the image compression. At the same time, the human's vision is not sensitive to the sharp change of edge (visual masking effect) and the color identification ability is not very strong. For these characteristics, we can reduce appropriately the coding accuracy in the corresponding

part, which can make a person not feel that there is a drop in the quality of the image for the vision. Then, we can achieve the aim of the digital image compression.

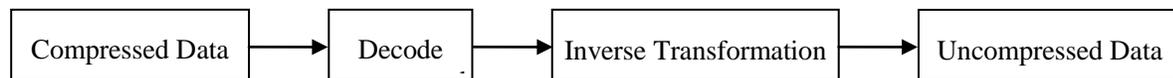
In many image compression methods, the usually used technique is to directly remove the information redundancy of the image itself and how to increase compression rate by adding the information redundancy to an image before it is compressed is never considered. If we compress the image by traditional methods without increasing redundancy degree of the image, so the compression effect has been curbed and the further improvement of the compression ratio is extremely difficult to be achieved.

a. Image Compression Method Based on Fuzzy Transformation

In the traditional image compression methods, the lossless compression is to directly encode the image by using encoder such as the entropy encoder and its compression rate is lower. In order to improve the image compression ratio, lossy compression is usually adopted and its compression and Decompression principles can be described as shown in figure 1.



(a) The Traditional Image Compression



(b) The Traditional Image Decompression

Figure 1 The Traditional Image Compression and Decompression Principles

In figure 1, the transformation is the orthogonal transformation which can remove the correlations among the adjacent pixels of an image, such as discrete cosine transform, wavelet transform and so on. These transformations are usually completely reversible, namely, if we only carry out the orthogonal transformation to an image, the inverse transformation can restore the original image without distortion. Quantification is a process of amplitude discretization. It is irreversible and lossy. Encoding is to assign a code for each symbol exported by the quantizer. The process is lossless, namely encoding and decoding is a reversible process.

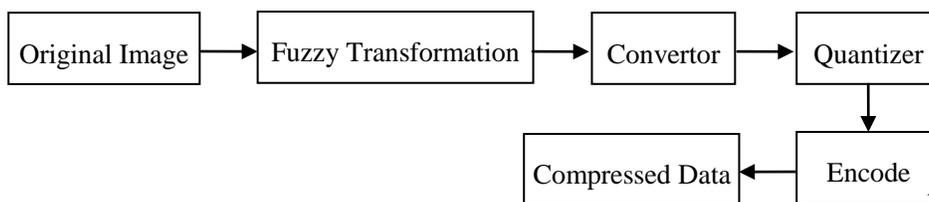
According to the above process, it can be seen that the transformation is a key step in the traditional image compression methods. It determines the removal degree of image correlations. However, the correlation is basically determined as soon as the original image is given. If we does not make any processing to the image, it will be very difficult to improve the efficiency of compression by the traditional orthogonal transformation methods. According to the image entropy coding theory, if the image entropy is low, the redundancy of information is big, then the compression rate of image data will be high. on the contrary, the data compression ratio will be low. According to the mathematical properties of entropy, the entropy will take the maximum when the image data are distributed with equal probability and takes the minimum, namely, equals to 0 when the probability of the image data equals to 1. Meanwhile, the following equation is satisfied.

$$H_N(p_1, p_2, \dots, p_{N-1}, p_N) = H_{N-1}(p_1 + p_2, p_3, \dots, p_N) + (p_1 + p_2)H_2\left(\frac{p_1}{p_1 + p_2}, \frac{p_2}{p_1 + p_2}\right). \quad (1)$$

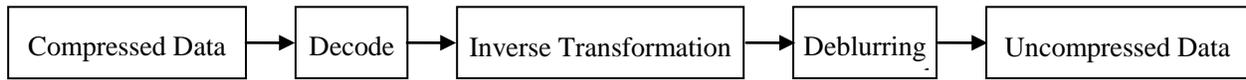
Since $p_1 + p_2 > 0$, then we can get

$$H_N(p_1, p_2, \dots, p_N) > H_{N-1}(p_1 + p_2, p_3, \dots, p_N).$$

That is to say, the more fuzzy the resolution of random field is, the less the average amount of information is for the random field of image. Although we can not prove theoretically whether the probability distributions satisfy equation (1) for all images, but a lot of experimental datum have shown that after fuzzy processing, the blurred image entropy is lower than that of the original image for most of the images, but the compression ratio of blurred image is higher than that of the original image. For this reason, we introduce a fuzzy processing in the traditional image compression method, namely we firstly carry out uniform fuzzy pretreatment for the original image, then orthogonal transform, quantization and encoding. Meanwhile, we introduce image deblurring in the process of decompression. Two implementation processes are shown as in figure 2.



(a) The Improved Image Compression



(b) The Improved Image Decompression

Figure 2 The Improved Image Compression and Decompression Process

b. Image Fuzzy Transform and Deblurring

According the unchangeable linear displacement degraded image model in image restoration, fuzzy transformation of the image can be described as

$$g(x, y) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(\alpha, \beta) \eta(x - \alpha, y - \beta) d\alpha d\beta, \tag{2}$$

where g indicates the blurred image and f indicates the original image, h is a point extension spread function of fuzzy system.

1) Fuzzy Transform of the Discrete Image

For the case of discretization, g and h sampling in the same interval and get the corresponding arrays $[f(i, j)]_{A \times B}$, $[h(i, j)]_{C \times D}$ and $[g(i, j)]_{A \times B}$. Augment these arrays with zero padding to get $[f_e(i, j)]_{M \times N}$, $[h_e(i, j)]_{M \times N}$ and $[g_e(i, j)]_{M \times N}$, namely,

$$f_e(i, j) = \begin{cases} f(i, j), & 0 \leq i \leq A-1, 0 \leq j \leq B-1, \\ 0, & A \leq i \leq M-1, B \leq j \leq N-1, \end{cases}$$

$$h_e(i, j) = \begin{cases} h(i, j), & 0 \leq i \leq C-1, 0 \leq j \leq D-1, \\ 0, & C \leq i \leq M-1, D \leq j \leq N-1, \end{cases}$$

$$g_e(i, j) = \begin{cases} g(i, j), & 0 \leq i \leq A-1, 0 \leq j \leq B-1, \\ 0, & A \leq i \leq M-1, B \leq j \leq N-1 \end{cases}$$

where $M = A + C - 1, N = B + D - 1$. Then, the image fuzzy model of (2) become

$$g_e(k, l) = \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} f_e(i, j) h_e(k-i, l-j). \tag{3}$$

If we express $[f_e(i, j)]_{M \times N}$, $[h_e(i, j)]_{M \times N}$ and $[g_e(i, j)]_{M \times N}$ as vector forms in row, then (3) can be expressed as

$$g_e = H_e f_e, \tag{4}$$

where H_e has a special structure as

$$H_e = \begin{bmatrix} H_0 & H_{M-1} & H_{M-2} & \cdots & H_1 \\ H_1 & H_0 & H_{M-1} & \cdots & H_2 \\ H_2 & H_1 & H_0 & \cdots & H_3 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ H_{M-1} & H_{M-2} & H_{M-3} & \cdots & H_0 \end{bmatrix},$$

and

$$H_i = \begin{bmatrix} h_e(i,0) & h_e(i,N-1) & h_e(i,N-2) & \cdots & h_e(i,1) \\ h_e(i,1) & h_e(i,0) & h_e(i,N-1) & \cdots & h_e(i,2) \\ h_e(i,2) & h_e(i,1) & h_e(i,0) & \cdots & h_e(i,3) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ h_e(i,N-1) & h_e(i,N-2) & h_e(i,N-3) & \cdots & h_e(i,0) \end{bmatrix}.$$

That is to say, H_e is a block circular matrix and can be expressed as

$$H_e = WDW^{-1} \tag{5}$$

where W is a matrix which is composed of eigenvectors of H_e , D is a diagonal matrix whose diagonal elements are composed of K times elements of $[H(u,v)]_{M \times N}$ obtained by two-dimensional Fourier transform of augmented matrix $[h_e(i,j)]_{M \times N}$ of the system impulse response and these elements are arranged as

$$KH(0,0), KH(0,1), \dots, KH(0,N-1), KH(1,N-1), \dots, KH(M-1,N-1).$$

The value of K depends on the layout of Fourier transform coefficient. Let

$$\varphi(u,v) = \sum_{i=0}^{M-1} \sum_{k=0}^{N-1} f(i,k) e^{-2\pi j \left(\frac{iu}{M} + \frac{kv}{N} \right)}, \tag{6}$$

Then, the relationship between K and the layout of transform coefficient is

$$K = \begin{cases} 1, & F(u,v) = \varphi(u,v), \\ \sqrt{MN}, & F(u,v) = \frac{1}{\sqrt{MN}} \varphi(u,v), \\ MN, & F(u,v) = \frac{1}{MN} \varphi(u,v). \end{cases} \tag{7}$$

Substitute (5) into (4), then let W^{-1} multiply left both sides, we can get

$$W^{-1}g_e = DW^{-1}f_e. \tag{8}$$

Wiener filtering is carried out in frequency domain of the image. Suppose that the original image f and noise n are independent, the transfer function of wiener filter is

$$P(u, v) = \frac{H^*(u, v)}{|H(u, v)|^2 + \gamma} \quad (12)$$

where $H(u, v)$ indicates the frequency domain of degradation point extension function, $H^*(u, v)$ is the complex conjugation of $H(u, v)$.

$$\gamma = \frac{S_m(u, v)}{S_f(u, v)},$$

where $S_m(u, v) = |N(u, v)|^2$ is the power spectrum of noise and $S_f(u, v) = |F(u, v)|^2$ is the power spectrum of the original image. In the frequency domain, the estimated value \hat{f} can be obtained as

$$\hat{F}(u, v) = P(u, v)\hat{G}(u, v). \quad (13)$$

III. OBJECTIVE ASSESSMENT METHODS OF IMAGE COMPRESSION QUALITY

The objective assessment methods of image quality can be divided into three categories based on the amount of original image or reference image information used by algorithms [8-13]. The first one is called the full reference method, which depends on the full reference image, such as mean square error method (MSE) and peak signal to noise ratio (PSNR) method based on pixel error statistics algorithm, information fidelity method based on information theory, the algorithm based on structural similarity index (SSI) or human visual system (HVS) and the algorithm combined with other algorithms etc. The second one is called the reduced-reference method, which depends partly on the reference image, such as the method based on the characteristics or wavelet domain statistics model or digital watermarking of original image, etc. The last is called the no-reference method, which is independent of the reference image, such as the method based on deviation level of statistics variables or Markov random field or machine-learning or weak digital watermarking algorithm (WIQM) or local statistics, etc.

a. The Traditional Objective Assessment Methods

The objective assessment methods of the image compression quality most widely used for a long time are based on error statistics. The following lists several commonly used traditional objective assessment methods [14]:

(1) Mean square error (MSE): let the size of the image $M \times N$, then MSE is defined as

$$MSE = \frac{1}{MN} \|f - \hat{f}\|^2 \quad (14)$$

where f represents the original image and \hat{f} represents the distorted image.

(2) Peak signal to noise ratio (PSNR): PSNR is a classical index defined as the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. It can be denoted by

$$PSNR = 10 \log_{10} \frac{A_{\max}^2}{MSE} \quad (15)$$

where A_{\max}^2 represents the maximal value of image pixels. For example, if image pixels are represented by using 8 bits per sample, $A_{\max}^2 = 255$.

(3) Improve signal-to-noise ratio (ISNR):

$$ISNR = 10 \log_{10} \frac{\|g - f\|^2}{\|f - \hat{f}\|^2}. \quad (16)$$

(4) Structural similarity index(SSIM): SSIM is used to measure the similarity between two images.

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}, \quad (17)$$

where μ_x represents the average of x , μ_y represents the average of y . σ_x, σ_y represent the standard deviations of the original image and compressed image pixels, respectively. C_1, C_2 are positive constants which are chosen based on experience to avoid the instability of assessment.

These methods are simple and intuitive, but their results often do not agree with people's subjective visual effect. It is because the mean square error and peak signal-to-noise ratio only reflect the differences between original image and compressed image and can not reflect local pixels with big or small gray level difference, etc. If all pixels are treated in the same way, human visual characteristics can not be reflected well. One of standards of image quality assessment algorithms is whether their results are consistent with subjective assessment results.

With the development of compression technology, the error statistics methods combined with the human visual characteristics were introduced for image compression quality assessment. A large number of studies have shown that the assessment methods based on HVS are better than those not considering HVS [15]. Therefore, the combination of subjective and objective assessment algorithms will become a focus for the future image compression quality assessments. From the point of the research progress of image quality assessment, the current image quality assessment methods mainly are divided into two categories: the methods based on visual perception and the methods based on visual interest.

b. The Image Quality Assessment Methods Based on Visual Perception

The human eyes' visual effect on the degradation of images is determined by the sensitivity of the human visual system and the visual sensitivity is determined by vision cells [16]. In addition, the sensitivity of the human visual system is also affected by the local spatial frequency of images. A lot of experimental results have shown that the factors influencing the visibility of the pixel errors are the local environment around the errors, instead of the background environment of the entire image [17-19]. According to the above visual features, all sorts of HSV model are proposed and used to evaluate the quality of the image.

c. The Image Quality Assessment Methods Based on Visual Interest

The coding technology based on image content enlightens researchers to investigate the image quality assessment methods based on visual interest. According to visual psychology, vision is a positive behavior of feeling. When one observes and understands an image, he/she often is unconsciously interested in some of these areas known as "region of interest" (ROI) and the degradation of less interested region is sometimes imperceptible. An image quality assessment method based on visual interest is put forward in [20-21]: the human eye's interest in the ROI is highlighted by weighting the different areas of the image and approximately considered to be inversely proportional to the area. The experimental results show that the method conforms to subjective visual quality of the human eye to some extent. The problems of this kind of method are how to determine the region of interest, how to test the image when it contains multiple regions of interest and how to determine the weights of these regions, etc.

IV. THE BLIND ASSESSMENT METHOD OF IMAGE COMPRESSION QUALITY

The blind assessment method is to explore a kind of assessment method which can obtain the assessment results without the original image as the same as the results obtained by the method with the original image. Since there mainly are three problems in the process of reconstruction of the image: the fuzzy edges and details of the image, the introduced structural error and noise, the current assessment methods are mainly based on how to measure the details of the recovery image, the structural error and noise.

a. The Distortion Analysis of Reconstructed Image

In the process of image coding and transmission, the caused distortions are potentially such as the grain noise of flat zone, block structure, pseudo outline, edge blur and distortion, ringing effect and the combination of these above distortions. The degree of the visual obstructions caused by these distortions is different, for example, based on the same MSE, the square structure of orthogonal transformation will cause more distortions than the ringing effect in the sub-band coding and the fuzzy effect is more than grain noise.

The distortions are caused mainly on the one hand by the blur of reconstructed image which is caused as some high frequency information of image is discarded when it is compressed. Due to the nature of the human visual system, it is more sensitive to low frequency parts, which are flat zones, than the high frequency regions, which are the edges and texture details, so we often discard the high frequency information and retain the low frequency part when we compress an image. The blur of reconstructed image is caused by the loss of high frequency information. For some algorithms such as cosine transform (DCT) compression algorithm, due to block transformation, the high frequency information is discarded, for the reconstructed image, there will be block effect.

On the other hand, the distortions of reconstructed image are caused by the quantization in the process of image compression. Considering differential pulse code modulation (DPCM) as an example, the image distortions caused by quantization mainly have the following four classes.

1) Slope overload. At the boundaries whose gray levels vary in a large range, because the forecast may be much bigger than the largest gray, it will result in the bigger quantization noise. When we decode and reconstruct the original image, the boundaries will blur.

- 2) Grain noise. The absolute value of the smallest gray level is not enough small, although the absolute value of the prediction error in the graded or flat zone is small, but quantitative output are not enough small positive or negative values, in which of the situations when we decode and reconstruct the original image, granular thin spots will appear in the corresponding area.
- 3) False contour. False contour is that the contour design will appear in a flat area when reconstruct the image, because the quantitative range used by the prediction error with smaller absolute value is too big.
- 4) Edge busyness. There are fluctuant canine jagged edges on the borders in the reconstructed image. This is because of the quantification of noises.

b. The Blind Assessment Method of Image Compression Quality

The objective image compression quality assessment methods above mentioned mostly need some information of the reference image to some extent. However, in many practical applications, we often can not get the original image or the pay is too big to get the reference image. Therefore, we have to reduce or even remove the dependence on the reference image from our image compression quality assessment algorithm. And at the same time, the subjective assessment can evaluate reasonably the image compression without the reference image. So, researchers hope to have the image quality assessment method without original image or reference image which can directly evaluate the image compression quality.

The blind assessment methods are independent of the original image or reference image. Their results conform to the objective assessment methods which depend or partly depend on the original image or reference image and the subjective methods. Since there are mainly three problems in the process of the reconstruction of the image: the fuzzy of image edges and details, introduced structural error and noise, so the blind image compression quality methods mainly based on the measurement of the image detail recovery, structural error and noise.

In the existing blind assessment methods, the fuzzy level of image was evaluated by measuring edge extension in [22], but structural error didn't considered. In [23], the formulas of measuring edge clarity, random noise and structural noise level were presented, but the calculations were complicated and it was difficult to determine accurately the edge noise level and structural noise. A detailed noise ratio was defined in [24], but this definition for the distortion error was based on assumption of additive white noise, it didn't conform to the distribution of many structural errors

in the image and it was difficult to estimate the noise. The average of higher order detail cumulant is proposed as a measure of image in [25], this method could effectively overcome the effect of Gaussian noise, but it could do nothing about false contour and ringing. A blind image quality assessment method based on active characteristics learning framework and a method considering specific JPEG2000 compression were proposed in [26, 27], they were effective for some specific problems.

To design effectively the blind image compression quality assessment method, we firstly use image variance σ^2 to measure the image edges and details recovery. Considering the difficulties of the existing structural error positioning and measurement of reconstruction image, we don't directly measure the structural error. We notice that the structural error in the image compression was accompanied by the fuzzy image, that is to say, the reconstruction image with structural error has varying degrees of fuzzy. Generally speaking, the more serious structural error is, the more severe the image fuzzy is. This is caused by image compression nature. If we apply a fuzzy function to do fuzzy processing to all images, for the fuzzy images, the image variance will decrease and for the clear images, the image variance will increase. Therefore, we can use fuzzy function to do fuzzy processing to an image, and then determine the severity of the structural error by calculating image variance before and after fuzzy processing. The smaller image variances change, the more severe structural error is, and the greater image variances change, the slighter structure error is. From the results obtained by experiments, we found that the amount of variation of image variance is inversely proportional to the image compression ratio. Thus, we can use $\Delta\sigma_b^2$ to represent the amount of variation of image variances before and after fuzzy processing.

In conclusion, we define a new blind assessment method as

$$I = \sigma^2 \Delta\sigma_b^2 \quad (18)$$

where I is the assessment result for the reconstruction image.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

We choose four gray images shown in Figure 3 as samples to test our method. Their size all are changed to 256*256. For these images, we use SIC1 image compression software to compress them by different multiples, such as 10 times, 30 times and 50 times. The values of the variance

are obtained by add 1 to the corresponding image compression ratio. Thus, the values of I in (18) and PSNR in (15) obtained by calculations and the relations of the values of I and PNSR for every image are shown in Table 1.

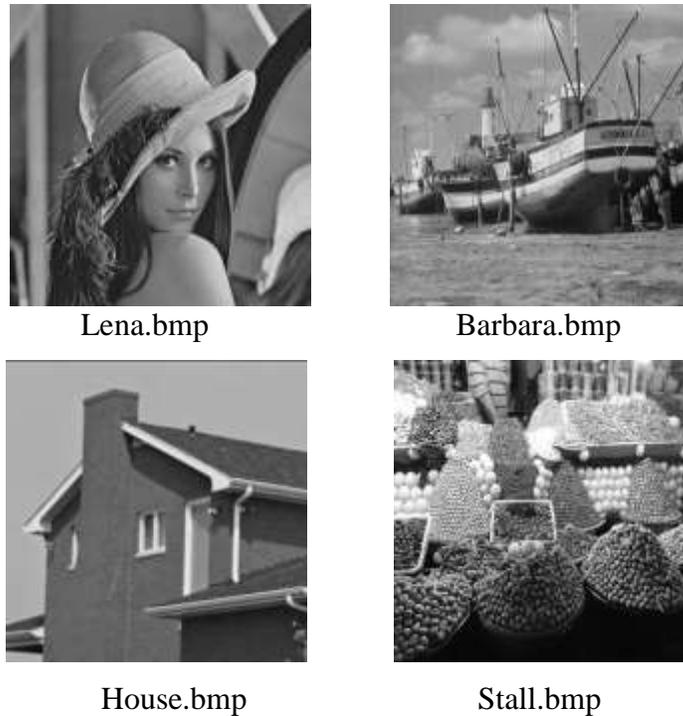


Figure 3. Sample images

Table 1. The Values of I and PSNR of Sample Images

	10 times		30 times		50 times	
	I	PSNR	I	PSNR	I	PSNR
Lena	5281	38.01	23369	30.81	3602	28.52
Barbara	29522	29.89	12549	24.55	6442	22.75
House	15903	39.49	3826	33.37	3003	30.27
Stall	143227	25.41	49894	21.09	17370	19.90

From Table 1, we can see that the values of I and PSNR both generally decrease with the increase of the image compression ratio. It shows that the blind assessment method proposed in this paper is an effective method.

IV. CONCLUSIONS

For image compression quality assessment in different applications, the image quality standards will be different according to different requirements. Although our method has a certain generality, it is difficult to establish a common image quality assessment system. For some images, it may be inapplicable, such as the results obtained by Lena.bmp shown in the first line of Table 1. Therefore, in order to get a more accurate assessment result, a variety of methods need to be considered simultaneously for a comprehensive evaluation. Blind assessment method has a relatively wider range of applications in the fields of image compression and image quality assessment. Now, it has been an important research direction of the image compression quality assessment.

V. ACKNOWLEDGEMENTS

This work was supported by Science Research Project of Hunan Province Education Office (14C0650) and Research Project of National University of Defense Technology (JC12 -02-01).

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