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A new method of Thangka image inpainting quality assessment ☆

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ABSTRACT

In order to solve the problem of Thangka image inpainting quality assessment (IIQA) and existing quality evaluation methods are not suitable for inpainting Thangka image, this paper proposes a new non-reference quality evaluation method which can effectively solve this problem. Firstly, due to lack of original Thangka image, the proposed method using symmetry of Thangka images to predicted an undamaged image. Secondly, we extract harries corner in Thangka inpainting images to show the structural feature of total graph. Thirdly, demonstrate subjective evaluation score of inpainting Thangka image by caparison difference of structural feature between inpainting and predicted original area. Finally, in order to compensate the lack of Thangka images in existing database, we add Generative Adversarial Nets (GANs) to generate large number of available image. Experiments show that our proposed method generates a state-of-the-art index for Thangka image inpainting quality which correlated with human vision.

1. Introduction

Thangka, also known as Thanga, is a scroll painting art created on a special cloth or paper, whose main purpose is to describe the history, culture and customs of Buddhism. Because it is influenced by history and religion factor, Thangka is listed as the first batch of state-level non-material cultural heritage in 2006. However, the most existing Thangka has been painted a long time ago, and many rare manuscripts have been damaged in various ways. With the development of computer science, many cultural relics are preserved by digital image. Using digital method to repair and manage damaged Thangka images which has great cultural value and social significance.

In recent years, the research of image restoration has made big strides. Total Variation (TV) [1] and Curvature Driven Diffusions (CDD) model [2] are most widely used in image restoration due to the simple calculation and wide application scope, as shown in Fig. 1. Fig. 1(a) is an original Thangka image. Fig. 1(b) is a damaged Thangka image. The green scratches on the head of the Buddha are damage area. In Fig. 1(c), the TV model can repair the scratches area of the head of the Buddha, but there are still coarse edges. Fig. 1(d) is the result of CDD model with distinct edges and little repair trail. This is because TV model can converts image restoration problem into functional problem, but ignores the contour geometry information of the image. However, CDD model takes curvature information of the contour area into consideration which makes the performance of repair better [3].

During protection and restoration of cultural relics, the efficacy of image inpainting quality affects later research a lot, such as Thangka image construction, Thangka image annotation and retrieval, etc. Where after, the method of significance map was proposed to evaluate the quality of image restoration [4], and the quality of image restoration was proposed through human visual density perception [5]. It is pointed out that although a large numbers of algorithms can inpainted effectively the damage image [6], it is rarely to describe the image inpainting effect in detail. To solve the problem, literature [6] proposed a new method which is named as image inpainting quality assessment (IIQA). Different from the original image quality assessment method, the main purpose of IIQA is evaluate the image quality of the repaired area, but traditional image quality assessment methods are dedicated to evaluating image quality in damaged areas. Therefore, the traditional image quality evaluation method does not apply to the quality evaluation of the inpainting image. Thus, IIQA has turned into an important research field in these years. With further development of IIQA, there are many new methods attached to image inpainting quality evaluation system. The experimental results show that these methods are feasible and reliable, but mostly of them are references or semi-references method.

Since the long history of Thangka image, some treasures have been damaged in varying degrees, and there is less information about the original image. Therefore, it is a great challenge to construct the non-reference Thangka image quality evaluation method. A method of evaluating the non-reference image inpaint-

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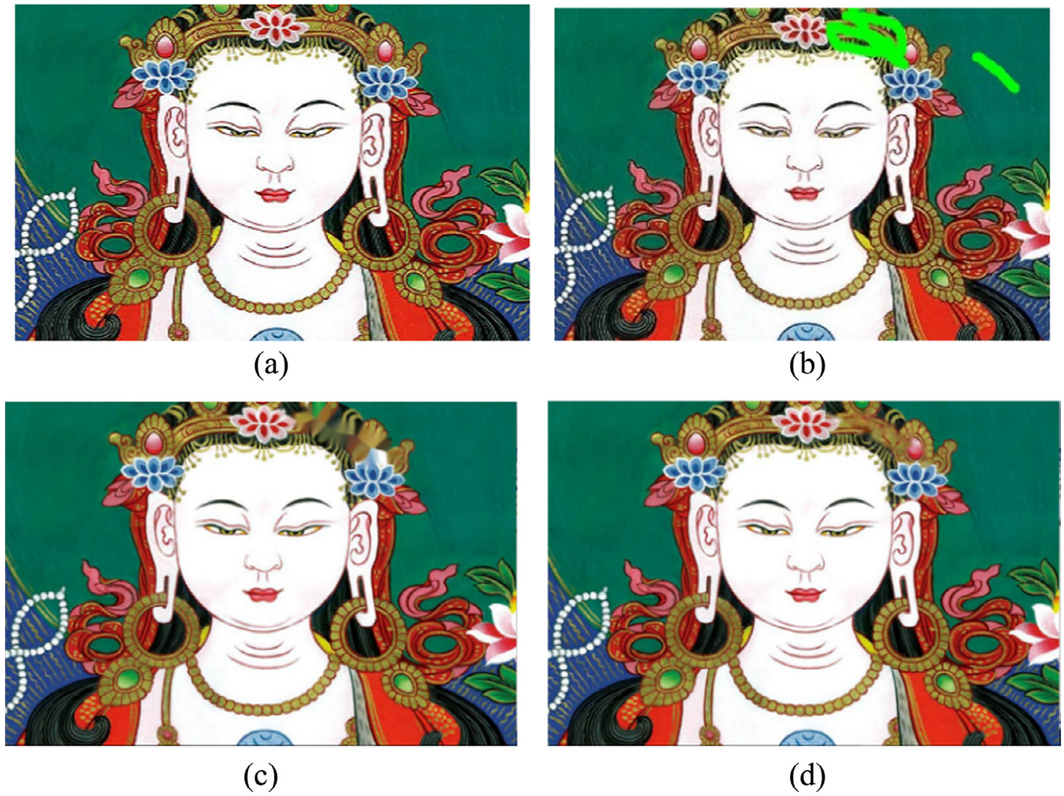

Fig. 1. Image restoration of damaged Thangka (a) original image (b) broken image (c) repaired image based on TV model (d) repaired image based on CDD model.

ing quality was proposed for calculating the variance of Eigenvalues in restoration area [7]. However, it only considers the structure information of the image and ignores other features such as the texture of the restoration area, which is not good to evaluate the quality of Thangka image restoration. Qureshi [6] indicated that this method is only suitable for smooth area of the image restoration quality evaluation. However, the Thangka image contains a lot of edge and architectural feature, and it is not good to use the method of literature [7] to evaluate the quality of the restored Thangka image.

After analyzing the above methods, this paper proposes a non-reference quality evaluation method of Thangka image restoration. This method considers the symmetry properties of most Thangka images, especially the Buddha, and use the symmetry of the image to predict the original image [8]. Then, the image quality evaluation model is constructed by extracting Harris interest points and quantifying the differences between predicted area and inpainting area. Besides, to solve the problem of limited Thangka dataset, we adopt Generative Adversarial Nets (GANs) to make image transformation and enlarge to obtain the information. We extend the database to make experimental result much reliable. Experimental results show that for Thangka image with symmetrical structure, our algorithm can obtain better results and the problem of the lack of original image is solved at the same time, and can effectively overcome the difficulties of the image which has multiple edges in image quality evaluation.

2. Correlation analysis of Tangka image features

2.1. Extraction of symmetrical features

The drawing of Thangka image is different from the ordinary natural image, and it follows certain composition and painting technique. These painting methods always divide in four classes, such

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as the central composition, the surrounding pattern symmetry, the central composition and the surrounding pattern asymmetry. According to the statistics Buddha statues, religious figures and historical figures have occupied more than 80% of the existing Thangka images [9]. Central composition is primary form in these kinds of paintings. Because of the special color and line characteristics of the Thangka image, its characteristic distribution has a certain rule. In the literature [8], it is proposed to predict the undamaged image and reconstruct the image by using the symmetrical features of Thangka. In the process of image restoration quality evaluation, this characteristic can also be used to predict the reference image. In order to extract the symmetrical features of the Thangka image, this paper mainly chooses the image of the central composition and the symmetry of the surrounding pattern as the object of study.

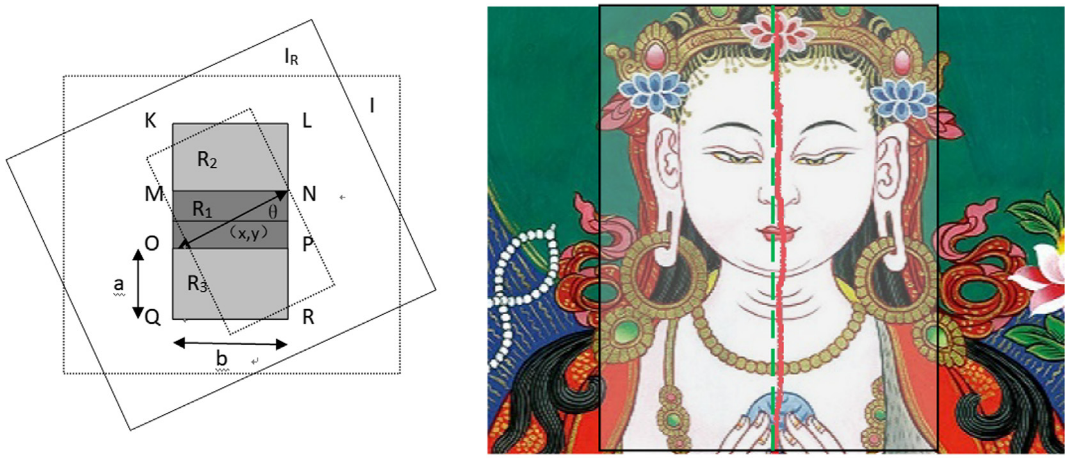
The composition of Thangka image is rigorous but its edge and texture are very complex. It cannot be used to distinguish the symmetry axis from the image through a single underlying feature. For this purpose, this paper adopts the symmetry axis to discriminate method based on the low level cue characteristics [10]. The feature extraction process is as follows:

(1) Setting the symmetric model.

Four symmetrical templates are set as shown in Fig. 2. To extracting feature of a certain pixel, we make a rectangle *KQRL* of $3a$ and b center on this pixel.

(2) Changing the template scale.

The rectangular *AGHB* is divided into three small ones named *KMNL*, *MOPN* and *OQRP*, which have a width of a, b, and change a, b and θ to obtain multiple symmetric models. Thus, the multi-scale and multi-angle symmetric features are calculated in the global image.



(a) (b)

Fig. 2. Symmetrical division of the image (a) Rectangular template for calculating symmetric features (b) symmetrical division and symmetry axis fitting.

(3) Calculating the eigenvalue.

Calculate the underlying descriptors histogram *R1*, *R2* and *R3* of the rectangular *KMNL*, *MOPN* and *OQRP*. And then calculate the distance between the histogram of their underlying descriptors by using the method [11]. The calculation as follows:

$$H_{i,j}(x,y,\theta,s) = \frac{1}{2}\sum_{1}^{k}\frac{(R_i(k)-R_j(k))^2}{R_i(k)+R_j(k)} \quad i,j=1,2,3, \tag{1}$$

where *s* represents three scales of the feature in Thangka inpating image such as brightness L, color C and texture T. θ is different direction of the feature. When the difference eigenvalue of the pixel is exceed a certain threshold, we can regard this pixel as the point on the axis of symmetry. The result was shown in Fig. 2(b).

However, it can be seen from Fig. 2(b) that the preliminary symmetric features is rough and does not meet the requirements of the symmetric axis. In order to solve this problem, this paper uses LS (least Squares) to obtain the fitting curve of symmetry points:

$$a = \frac{\sum xy - \frac{1}{N}\sum x\sum y}{\sum x^2 - \frac{1}{N}(\sum x)^2} \tag{2}$$

$$b = y - ax \tag{3}$$

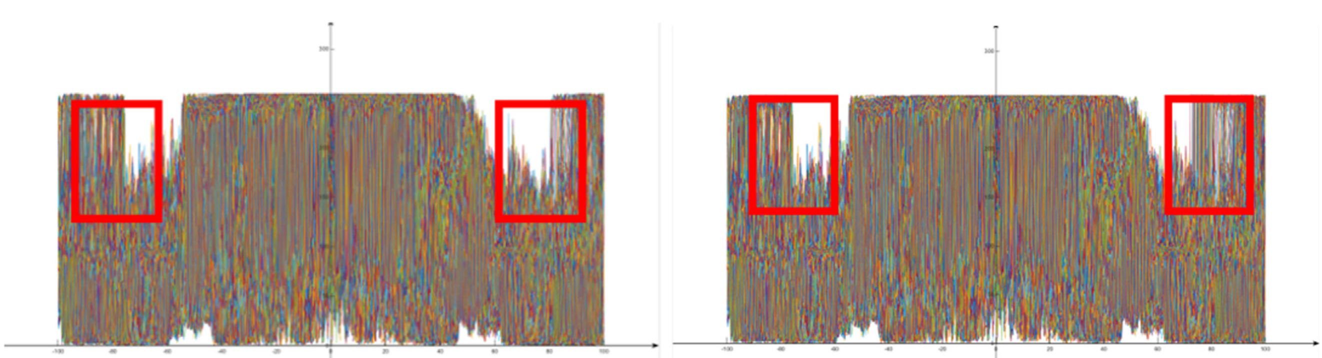
The modified result is shown in Fig. 2(b). The green line symbolizes preliminary symmetric features and the red line is new axis which generated based on formula (2) and (3). The specific process is as follows:

(a) After fitting the coordinate of symmetric points are M (x_1,y_j) $j = 1,2,3,4,\ldots,J$ is assumed;
(b) Regarding the symmetric line after fitting as y axis and the new coordinates of pixels is m (x_u, y_v), formula is defined as:

$$x_u = x_r - x_1 \tag{4}$$

$$y_v = y_j \tag{5}$$

Fig. 3 shows the translation of coordinate axis in Fig. 2(b). It can be seen from Fig. 3 that the axes divide the image into left and right parts, and the shape features of the images is symmetry. Fig. 3(a) is the original image through the symmetrical segmentation and distribution of symmetrical area is same. The red box in Fig. 3(b) is repaired image after symmetry segmentation. By comparing Fig. 3(a) and (b), the red frame (repaired area) on the right side is very different from the pixel distribution of the left red frame (lossless area). However, there is almost no difference in the pixel distribution of the red frame on the left side in Fig. 3(a) and (b).



(a) (b)

Fig. 3. Symmetry axis conversion (a) undamaged image (b) repaired image.

Thus, the above method can extract the Thangka image symmetrical features. The symmetry features is utilized to get the undamaged area, which is served as original image. It was in this way that the experiment was made, which overcome effectively the shortcoming of lack of reference image.

2.2. Extraction of harries interest point

The researches of the Human visual system (HVS) show that the observer is more concerned with the structural information of the target in the visual field, such as the edge or contour information in the image. In general, in order to solve the problem of eigenvalue extraction in image quality evaluation, all existing edge information in the image should be detected. But image edge character only considered in x or y direction which has a larger variation points. Harris [12] proposed a method to extract image feature by using the Harris corner point, which mainly extracts the location of pixels that the neighborhood matrix of the x, y axis directions having large changes. Compare with the edge, corner point features have many advantages such as good invariability, simple calculation and intuitive representation. The process is as follows:

(1) The Harris operator uses a Gaussian window $w(x, y)$ instead of a binary window, which makes to add greater weight for every pixels that are closer to the center point and reduce noise effects. The formula is:

$$w(x,y) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2} \tag{6}$$

(2) Calculate the correlation matrix of each pixel where Ix and Iy are the feature vectors of horizontal and vertical directions [12]. This is:

$$A = w(x,y) \otimes {I_x}^2 \tag{7}$$

$$B = w(x,y) \otimes {I_y}^2 \tag{8}$$

$$C = D = w(x,y) \otimes ({I_x}^2 {I_y}^2) \tag{9}$$

$$M = \begin{pmatrix} A & B \\ C & D \end{pmatrix} \tag{10}$$

(3) Counter the response value of Harris point in Thangka image.

$$R = (AB - CD)^2 k(A+B)^2 \tag{11}$$

And find the maximum value R_{max} in the local range. If the response value is greater than the threshold, it is considered as the corner point.

Gray level histogram and its equalization can intuitively reflect the pixel brightness, distribution and statistical characteristics of image. Fig. 4(a)–(d) shows the gray level histogram and its equalization which extracted from the original, broken and two repaired image in Fig. 1. Compared with the original image in Fig. 4(a), the corner points of the damaged area in Fig. 4(b) increase significantly. In Fig. 4 (c) and (d), the numbers of corner points in the restoration area are decreased, and the effect is more obvious in Fig. 4(d). It can be seen that the corner point feature can reflect directly the difference of varied restoration images. Rudner [11] pointed out that the corner point directly extracts the eigenvalues of the neighborhood matrix of pixel points, and which is much closer to the visual characteristics of the human eyes. So it is more consistent with the requirements of feature extraction in image inpainting quality evaluation methods.

2.3. Evaluation index

As noted in previous paper, the corner point is more consistent with the visual characteristics than the edge. Therefore the difference between the predicted value and the actual value can be quantified by extracting the corner point. However, this feature only considers the structure characteristics of the image and cannot directly predict original image. Based on the symmetry of the Thangka image, this paper presents an index which uses different location of harries point between inpainting area and undamaged area. The calculation procedure is as follows:

(1) Build undamaged image for Thangka image.

The inpainting image is segmented by using the symmetry of the Thangka image. The repaired image is transformed into the coordinate system, and the Y-axis is used to divide the image into the left and right parts. For better and more convenient calculation later, all pixel x are converted to symmetric points around the origin of the coordinate axis.

(2) Extraction of corner points for restoration images.

Using the Gaussian sliding window of 7×7 to identify the Harris points of the image, feature vectors of Ix and I_Y are used to represent the two directions of the fastest and the slowest. If both of them are fast, the faster one is regarded as the marginal area, and Harris point coordinates are also placed in the symmetric coordinate system. The updated coordinate is $j\ (x_j, y_h)$, and the Angle is obtained from the origin $c\ (x_c, 0)$. In the experiment, the search weight value of the corner point is 0.1, and the image scan is only for eight neighborhood range of each pixel.

(3) Calculate the difference sore between the predicted image and inpainting image.

After transformation of coordinate, we calculate the distance between updated point $j(x_j, y_h)$ and the origin point $c(x_c, 0)$. w_1 are the distance of the Harris point in predict area and w_2 are the distance of the Harris point in inpainting area, which are defined as:

$$w1 = \sum_{j=1}^{\frac{1}{2}k} \sqrt{x_j^2 + y_h^2} \tag{12}$$

$$w2 = \sum_{j=\frac{1}{2}k+1}^{k} \sqrt{x_j^2 + y_h^2} \tag{13}$$

And the difference between distance of predicted image and the inpainting image is worth to the image restoration evaluation index H. That is:

$$H = |w_1 - w_2| \tag{14}$$

The above method is consistent with other feature extraction methods, but the algorithm using symmetrical characteristic of the Thangka, by contrast, which shows the difference of the image and undamaged area effectively, overcome the difficult of without original images.

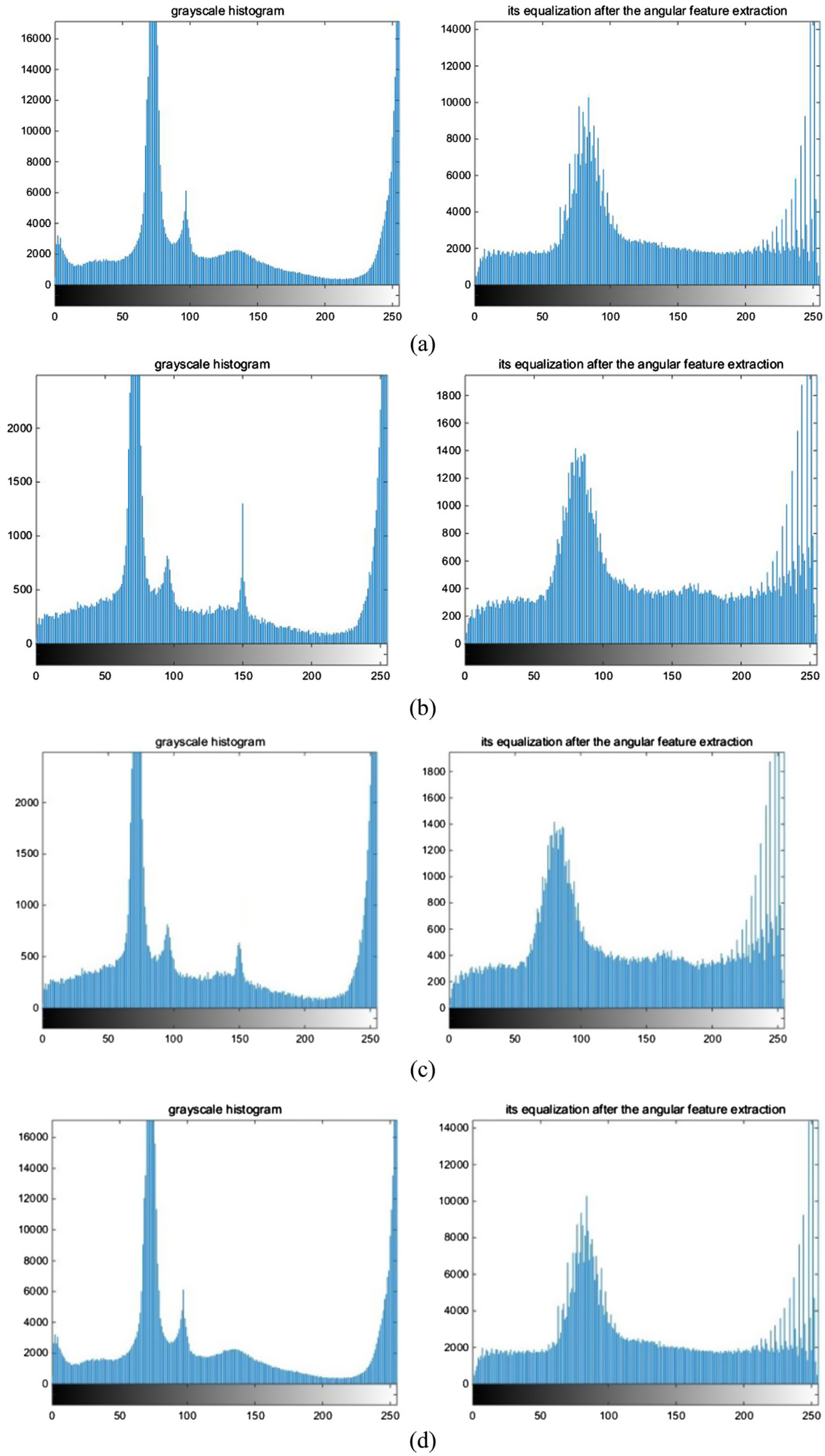


Fig. 4. The grayscale histogram and its equalization after the angular feature extraction. (a) Original image (b) damaged image (c) repaired image of TV model (d) repaired image of CDD model.

3. The experimental results

Since there is no standard system for Thangka image database, the author select 100 images which are repaired and damaged in different degree from Thangka database from network and school. The database contains 30 JPEG compression images, 30 PNG compression images and 40 JPEG 2000 compression images with a uniform size of 303×448. At the same time, five observers were asked to rate and calculate the MOS (Mean Opinion Scores) of each image.

Before doing the experiment, some preprocessing was carried out for the images in the existing Thangka image database. Due to lack of Thangka image, we use GANs (Generative Adversarial Nets) according to different levels of image distortion to enlarge the database. Usually we process images by some method, such as flip which can form a large number of reliable experimental data. The specific process is as follows:

(1) In the first place, we set a generated model $G(z)$ and a discriminate model $D(x)$ and we assumption that they are created without any limitation.
(2) Generate randomly a set of vectors and set it as the input vector of the generated model, which is denoted as $D(x)$.
(3) Select the image from the existing Thangka database as x.
(4) Set discriminate network $D(x)$ or x as input of loss function. Input value has turned into a number between 0 and 1 through the loss function, and then using it to training lowest functional value by many times to achieve the purpose of get most similar pictures. The formula is as follows:

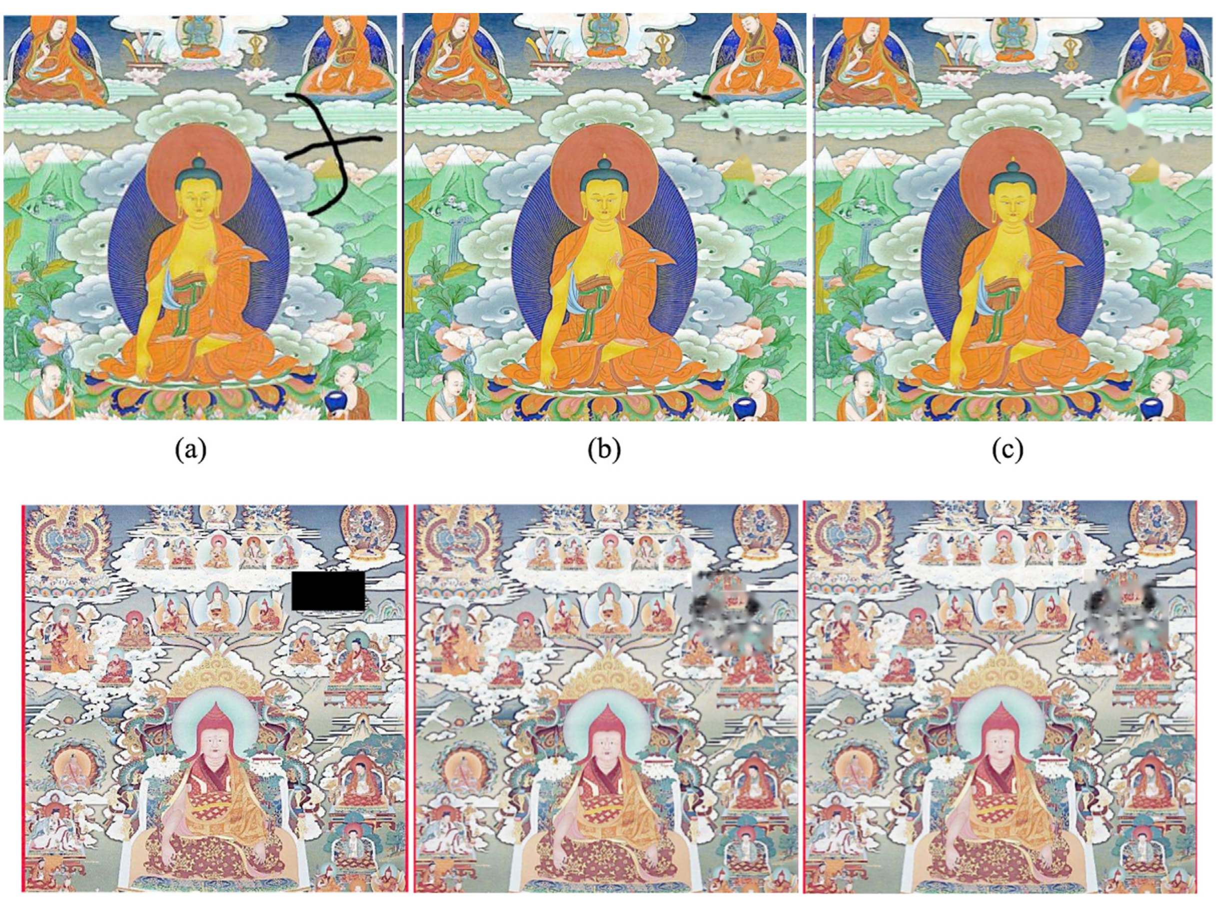
$$-((1-y)\log(1-D(G(z)))+y\log D(x)) \tag{15}$$

3.1. Experiments on different repair algorithms and different degrees of restoration images

Sometimes we also want to compare the performance between new and existing algorithm. In the experiment, the TV model and CDD model were selected to repair Thangka damage images. PSNR、DN [13], GD [14] and BorSal [7] was used to evaluate performance of each model objectively. Among these methods, PSNR,

Table 1
The result of CDD model in different degrees.

Model name	Repair scale	Subjective Score	PSNR	DN	GD	BorSal	New algorithm
CDD model	Repair scale 80%	0.8288	23.457	0.8911	0.8343	82.78	5.7892
	Repair scale 95%	0.9505	24.519	0.9345	0.9244	91.33	4.0891
TV model	Repair scale 80%	0.8032	25.889	0.8678	0.8432	80.89	7.9760
	Repair scale 95%	0.9266	25.231	0.8833	0.9164	91.87	7.2396



(a) (b) (c)

(d) (e) (f)

Fig. 5. Comparison of different algorithm performance (a) Scratches image (b) 80% restoration image (c) 95% restoration image (d) Image of block damage (e) 80% restoration image (f) 95% restoration image.

Table 2
Performance comparison of different evaluation methods.

Model	SROCC	KROCC	PLCC
PSNR	0.8638	0.7877	0.8094
SSIM	0.9142	0.8281	0.8431
PWIIM	0.8935	0.8646	0.8831
ASVS	0.9291	0.9040	0.9163
DN	0.8983	0.8727	0.8879
GD	0.9273	0.9172	0.9363
BorSal	0.9238	0.8399	0.9256
New algorithm	0.9377	0.8508	0.9330

DN and GD are reference image quality assessment (IQA) methods. Specifically, DN and GD are IIQA metrics. BorSal is no reference IIQA. To demonstrate the superiority of the new algorithm, we add one more experiment by using Thangka images which are repaired in different degrees. There are 2 inpating degrees such as 80% and 90% in this test, the results were shown in Table 1.

As we can see, Fig. 5(a) and (d) are the Thangka images with scratches and block damage, and the location of damage is mainly concentrated in complex areas such as the headwear and face of the Buddha. The Inpainting images that are repaired by the CDD algorithm are shown in Fig. 5(b) and (c). It can be seen from the figure that the scratch area are restored better, but the edges area are still discontinuous in Fig. 5(b) which is repaired in 80% degree. Fig. 5(c) shows the image which is repaired in 95% degree, the scratch areas are basically repaired and the edge areas are fully connected. The images are reconstructed by the method which is named TV model, as shown in Fig. 5(e) and (f). In Fig. 5(e), the repaired effect is poor in the image which is repaired in 80% degree, and there is a large amount of block damage in the characters. Fig. 5(f) is the image which is repaired in 95% degree, but there still have a lot of fuzzy blocks at the edge areas.

Combined with the data in Table 1, PSNR is IQA method and not consider the image structure information such as edges in Thangka images, as shown in Table 1. So the phenomenon of "high score and poor quality" has appeared in PSNR and demonstrates the IQA metric can not apply to inpating image. The new algorithm combines multi-scale structural features such as Harris point and symmetry feature, and the results of assessment is more relevant to image restoration. Therefore, the algorithm is more sensitive to image structure.

3.2. Compared with SSIM, BorSal and PSNR.

Increase IQA method SSIM [15], reference IIQA method DN[13], GD[14], PWIIM[16], SVS[17], and the non-reference IIQA method

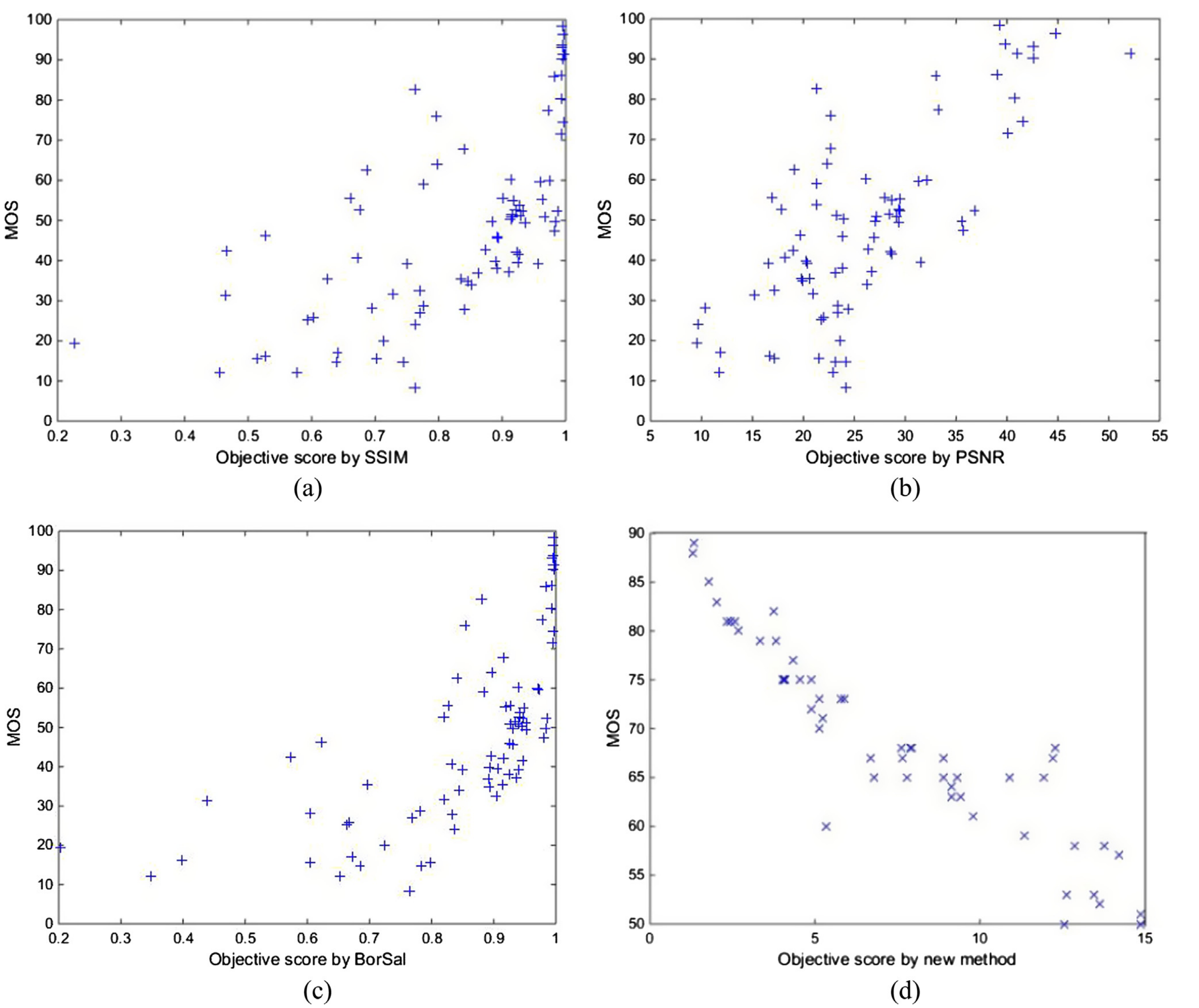


Fig. 6. Scatter plots of subjective mean opinion score (MOS) versus model prediction (a) SSIM (b) PSNR (c) BorSal (d) new method.

BorSal [7] to compare performance with the new algorithm, and SROCC (Spearman rank order the correlation coefficient), KROCC (Kendall rank - order the correlation coefficient), PLCC (Pearson linear correlation coefficient) is used as an objective parameter to evaluate the performance of each algorithm. The calculation results are shown in Table 2. Can be seen from Table 2, new algorithm is better than other method in almost every index, but there still have a little difference with GD method. It is obviously that the new algorithm is a kind of no reference evaluation method. The other three kinds of method need to be provided the reference image. As a whole, new algorithm is superior to other algorithms in this paper.

3.3. Correlation between algorithm and MOS

At last, combined with the subjective evaluation index of MOS (Mean Opinion Scores), four methods and the correlation of MOS scatter plot has shown in Fig. 6. It can be seen from Fig. 6 that the evaluation index of this paper is more consistent with MOS, slightly better than BorSal and SSIM, and PSNR has the worst effect.

4. Conclusion

In this paper, we have proposed a non-reference image inpainting quality evaluation method by combining the symmetry of Thangka image with Harris Conner point. Due to lack of Thangka image database, we add a new method named GANs to extend the experimental data. The result is shown that the new method has solved some problem in exist image inpating quality evaluation method especially in complex area. Experimental demonstrate that the new algorithm can get better performance than state-of-the-art methods, even including some reference IIQA metrics. As a next step, we plan to build a complete Thangka image database to make new method become more credible.

Conflict of interest

There is no conflict of interest.

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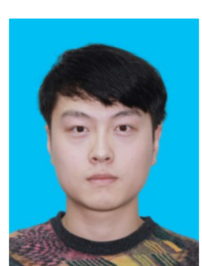

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