Study on Digital Image Inpainting Method Based on Multispectral Image Texture Synthesis

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ABSTARCT: *Digital image inpainting method based on multispectral image texture synthesis is proposed for the digital archives and high fidelity replication of defective Painting Arts. Firstly, multi-channel images of Painting Arts are obtained through multispectral technology. Inpainting technique based on texture synthesis is adopted for the multispectral reconstruction image. In the process of inpainting, the improved Criminisi algorithm is adopted to calculate the image gradient based on IHS space. It avoids wrong information propagation caused by the difficulty of direction matching and inaccurate gradient calculation of the correlation of color components in the RGB space. It can reduce the mismatch of the color patches in the inpainting area and pseudo color, and improve the digital inpainting quality of multispectral images. It has been proved that MSE of multispectral images inpainting qualities is 5.4021 and PSNR of multispectral images inpainting qualities is 41.6320, so improved Criminisi algorithm is superior to traditional image inpainting algorithm. It provides a reliable basis for digital inpainting, digital archives and high fidelity replication of defective Painting Arts.*

Subject Categories and Descriptors
I.4 [Image Processing and Computer Vision]; I.4.7 [Feature easurement]; Texture: **I.3.4 [Graphics tilities]; Paint Systems**

General Terms: Image Analysis, Texture Processing, Criminisi Algorithm, Inpainting method, Multispectral image texture synthesis

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1. Introduction

As a treasure of human civilization, especially the painting and calligraphy of ancient dynasties, traditional Chinese painting and murals and other works of art, Painting Arts has immeasurable artistic value. However, there are different degrees of damage because of the human, accident, natural environment and other factors. Accurate digital acquisition and effective inpainting treatment for Painting Arts can meet people's demands on artwork color accuracy and structural integrity. It is a research hotspot in the computer vision and image processing fields.

The acquisition technology of traditional images is based on RGB three-channel chroma information; it can't characterize color information of the Painting Arts objectively. This method is limited[1]. Multispectral images not only record image details clearly, but also have more abundant information than general images. Multispectral images contain multi-dimensional spectral information in addition to ordinary two-dimensional images[1,2], and record details and colors of Painting Arts by abundant information, and provide a better foundation for digital archive work of Painting Arts.

Traditional image inpainting is direct inpainting to the original image, and repaired mainly by hand[3,4] in order to restore image defective area so that the images which have been damaged or have been repaired cannot be perceived for an observer. However, traditional inpainting work is not reversible. There is a certain risk. With the development of digital technology, people could execute digital virtual inpainting[5] by computer. There is no risk. What is more it can adjust the repairing results repeatedly according to the demands. The method of texture information synthesis based on sample blocks is adopted in this paper. In the inpainting process, it calculates image gradient based on IHS space. It avoids wrong information propagation caused by the difficulty of direction matching and inaccurate gradient calculation of the correlation of the color components in the RGB space, reduces error matching and pseudo color in inpainting areas. It achieves better inpainting effect. The method can provide a new way of technology for Painting Arts inpainting, and also provide a new idea of image acquisition and digital inpainting for Painting Arts high fidelity image reproduction.

2. Previous and Related Work

The early development of multispectral imaging technology mainly concentrated in developed countries, such as the Europe, America and Japan. The United States RIT Munsell color science laboratory obtained multi-channel data information of image through three channels of large array sensor combining with broadband absorption filter [6,7], and this system had the advantages of simple structure, high resolution, short image acquisition time and high applicability. Hardeberg and other scholars in Norway Gjøvik college obtained multidimensional spectral information of manuscript through the liquid crystal tunable filter (LCTF) [8-11] combining with a monochromatic camera, which the tunable filter could take sample at 10nm width in visible band. However, the multi-channel acquisition image would lose some information because of the tunable filter of this system being lower transmittance. Multispectral imaging system was built by the University of Aachen in Germany with 16 narrow-band interference filter with monochromatic CCD photosensitive surface arrays [12,13]. However, the uniformity of imaging color was not good because the interference filter used in the system has great limitations. Berns[14,15] analyzed spectral precision and color accuracy of above methods. The experimental results showed that the average color difference of original using broadband filter combining with tricolor photosensitive unit was less than 1, and the color difference between correction data and acquisition data was less than 1.5%, which was better than that of other more complex equipment. Since then, many famous research institutions in the world have borrowed the equipment structure of MCSL laboratory, so the broadband multi-channel system is used to obtain original image in this paper.

In 2003, Criminisi et al [16,17] proposed image inpainting algorithm based on sampling replication, which drew lessons from texture synthesis method to find the sample area and matching replication. This method automatically selected the matching area to copy, the inpainting effect of texture information was better, and it could also inpaint the larger area. In recent years, most of the researches on large area damaged images have been done using texture information synthesis method, and some achievements have been achieved. Cheng et al proposed an improved method on priority function because they found that the priority in the ongoing process of inpainting was no longer reliable through researching Criminisi algorithm and massive experiments, and made sure the effective and proper filling effect [18]. Shen J et al first solved the gradient of image known region, then obtained complete gradient according to the texture synthesis. They could got final inpainting results according to the gradient value combining to Poisson equation, but the inpainting would be blurred[19]. Li et al[20] proposed texture synthesis inpainting method based on sample block, which they detected incomplete convex structures by wavelet transform, and then completed the operation by linear fitting and expansion. Literature [21] proposed the definition of filling order priority and sample matching degree by structure tensor, and proposed a K-nearest neighbor algorithm to reduce computation amount of searching for the best matching block. Hareesh et al[22] introduced fractional order derivatives instead of gradient functions. They put forward a new function to decide the filling order priority that the new function is a linear combination of the local gradient at the pixel p on the boundary and logarithm of gradient, and good inpainting results are achieved. Xi et al[23] introduced a gray scale distribution aggregation feature through two-dimensional entropy displaying into the priority improvement formula in order to reduce the influence caused by the rapid decline of the confidence term in the image inpainting process. Qi et al [24] proposed an image inpainting algorithm based on sample structure features, which combined improved the priority function with new confidence term updating method, so it could overcome the shortcoming of texture rich region mismatching effectively.

3. Multispectral Image Acquisition and Spectral Reflectance Reconstruction

3.1 Multispectral Imaging System

On the assumption of the spectral imaging system being linear[25], the output response of the i th channel of the imaging system can be represented as the integral form:

$$g_i = \int_{\lambda_{min}}^{\lambda_{max}} l(\lambda)\, r(\lambda)\, f_i(\lambda)\, o(\lambda)\, s(\lambda)\, d\lambda + \varepsilon_i \qquad (1)$$

where $l(\lambda)$、$r(\lambda)$、$f_i(\lambda)$、$o(\lambda)$ and $s(\lambda)$ are spectral power distribution of lighting source, spectral reflectance of the surface of object, spectral transmittance of the i^{th} channel system filter, spectral transmittance of imaging optical path, spectral sensitivity functions of CCD, ε_i is the noise generated by the system, and the range of λ is generally 400nm-700nm.

The noise ε_i generated by the system can be removed by dark current removal and illumination nonuniformity correction, and obtained a linearized multispectral imaging system. Then the system response model (formula (1)) can be simplified to the following matrix form:

$$g = QR \tag{2}$$

where, g is the digital response of the i channel of camera; $R = [r_1, r_2,...r_n]$ is spectral reflectance vector, n is quantity of sample; $Q = [q_1, q_2,...q_n]$ is transition matrix

3.2 Spectral Reflectance Reconstruction Method Through the Principal Component Analysis

Principal component analysis (PCA) is a dimension reduction method which is often used in image processing. It could find a new orthogonal comprehensive index of each other through diagonalization of the covariance matrices of data set, and obtains the most information by limited projecting in the new index of the original sample data[26]. Singular value decomposition is conducted on spectral reflectance of training samples used PCA based on Spectral imaging system model of formula (2),

$$R_0 = USV^T \tag{3}$$

where U is feature vector of $R_0R_0^{\mathrm{T}}$, S is diagonal matrix which constitutes of characteristic values in descending order, V^T is feature vector of $R_0^TR_0$. If the cumulative contribution rate of the first k principal component eigenvalues

$$V_k = \sum_{i=1}^{k} \varpi_i / \sum_{i=1}^{m} \varpi_i \tag{4}$$

is large enough, then the spect ral reflectance can be considered to be a linear combination of k feature vector. The transformation matrix of training samples can be obtained by formula (5):

$$Q^+ = U_kS_kV^Tg_0^{\mathrm{T}}(g_0g_0^{\mathrm{T}})^{-1} \tag{5}$$

Where Q^+ is the pseudo inverse of the transformation matrix, $U_kS_kV^T$ is the spectral reflectance matrix of the first k principal component of training samples, $g_0^{\mathrm{T}}(g_0g_0^{T})^{-1}$ is the least square inverse of the training sample system response value. After the transformation matrix is found, spectral reflectance reconstruction can be carried out according to formula (6):

$$\hat{R} = Q^+g \tag{6}$$

Where $\hat{R}$ is spectral reflectance of reconstructed samples, Q^+ is the pseudo inverse of the transformation matrix, g is the camera response value of optimized of reconstructed sample.

3.3 Color Reproduction of Multispectral Images

The purpose of multispectral imaging technique is to obtain accurate color. Therefore, spectral reflectance should be converted to color values to achieve multispectral color reproduction after reconstruction the spectral reflectance of each point of the images. To calculate the color chromaticity coordinates, we must firstly calculate three stimulus value of color. Three stimulus values[27] based on CIE chromaticity system are shown in equation (7):

$$\begin{cases} X = k\int_{\lambda} s(\lambda)\rho(\lambda)x(\lambda)d\lambda \\ Y = k\int_{\lambda} s(\lambda)\rho(\lambda)y(\lambda)d\lambda \\ Z = k\int_{\lambda} s(\lambda)\rho(\lambda)z(\lambda)d\lambda \end{cases} \tag{7}$$

where the wavelength range of λ is 400nm~700nm, $s(\lambda)$ is the relative spectral power distribution of the light source, X、Y、Z are the three stimulus for color, $\rho(\lambda)$ is the object surface spectral reflectance, $x(\lambda)$、$y(\lambda)$、$z(\lambda)$ is the CIE standard colorimetric observer function.

The three stimulus value XYZ of the CIE chrominance system is the color space independent of display device. It can be converted to the color space value RGB of the display device, and to display the image color, as shown in the formula (8) [27]:

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{pmatrix} 0.032406 & -0.015372 & -0.004986 \\ -0.009689 & 0.018758 & 0.000415 \\ 0.000557 & -0.00204 & 0.01057 \end{pmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \tag{8}$$

After the spectral reflectance changes to the visible color space RGB, multispectral images can be displayed on an image display device.

4. Digital Image Inpainting Based on Texture Synthesis

4.1 Introduction of Digital Image Inpainting

The development of digital image inpainting technology is mainly divided into two categories[28]: one is image inpainting technology based on structural information inpainting for small damage scale. This technique was firstly introduced into the image processing by Bertalmio et al[29]. The other is sample block matching algorithm based on texture information synthesis for large damage scale. It was originally proposed by Criminisi[16,17] et al. It can obtain better inpainting effect and inpaint larger image area through automatically selecting the matching area.

In this paper, the image inpainting method based on sample block filling is used to repair the damaged area of multispectral images. Image inpainting algorithm based on the sample block is a method of filling inpainting based on isophote line driven which integrated partial differential equations (PDE) automatic diffusion with texture synthesis algorithms[30]. It can inpaint structure information and texture information at the same time. Therefore, it can avoid fuzzy phenomenon caused by structural inpainting based on PDE and structural information error in texture synthesis, and obtain ideal visial inpainting effect. However, the isophote line computation of this inpainting method is multi-band simultaneously processed based on RGB color space. We know that it is very difficult to accurately define direction matching degree because of the RGB channel correlation[4], so the image edge structure information is inadequate utilization, and it is easy to cause the information transmission error which makes color mismatching of filling areas, appears pseudo color, and affects digital inpainting quality of multispectral images. This paper proposes a channel transform method based on the Criminisi algorithm, which converted RGB color space to IHS color space by space transformation. It can obtain three unrelated components, brightness, saturation and chroma, then recompute image gradient values based on this three unrelated channels.

4.2 Digital Image Inpainting Algorithm

4.2.1 Introduction of Criminisi Algorithm

In 2003, Criminisi proposed an image restoration algorithm based on sample block filling[16]. It has a better inpainting effect of damaged image in large area. As shown in Figure 1, the inpainting process is as follows:

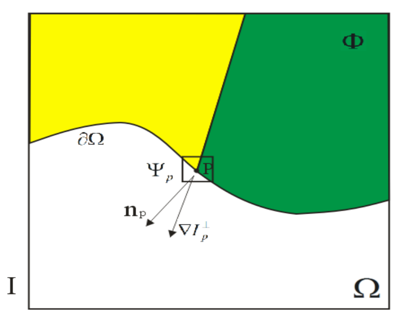


Figure 1. Schematic diagram of Criminisi algorithm

① Calculate the priority values for each pixel on the fill boundary $P(p)$. Then find the point p which has the highest priority and fix the pixel block ψ_p which is centered on p at first. The formula for $P(p)$ is as follows:

$$P(p) = C(p) \times D(p) \tag{9}$$

Where $C(p)$ is the confidence parameter and $C(p)$ is the initial confidence:

$$C(p) = \begin{cases} 1 \ \forall p \in \Phi \\ 0 \ \forall p \in \Omega \end{cases} \tag{10}$$

The confidence parameter is defined as:

$$C(p) = \frac{\sum_{p \in \Psi_p \cap \Phi} C(p)}{|\Psi_p|} \tag{11}$$

Where Ω is damaged area of the images, Φ is the undamaged area of the images, and $|\psi_p|$ represents the area of damaged block ψ_p in the damaged area.

$D(p)$ is the direction matching degree of point p:

$$D(p) = \frac{|\nabla I_p^{\perp} \times n_p|}{\alpha} \tag{12}$$

where n_p is the normal vector of the boundary of the damaged area and α is normalization factor (for common grayscale images, α is 255). $\nabla I_p^{\perp}$ is the isophote line vector of the point p (direction and intensity), and its direction is perpendicular to the gradient vector of the point p. Define it as:

$$\nabla I_p^{\perp} = \frac{(-I_y(p), I_x(p))}{\sqrt{I_y^2(p) + I_x^2(p)}} \tag{13}$$

②To find the candidate sample block which has the smallest sum of squares of color difference as the best match module ψ_q by calculating the square sum of color difference $d(\psi_p, \psi_q)$ of the known pixel corresponding to the sample block ψ_q and ψ_p the block to be repaired ψ_p. To fill the pixels to be filled in ψ_p to achieve the inpainting of structure and texture.

$$\Psi_q = \arg\min d(\Psi_p, \Psi_q) \tag{14}$$

$$d(\Psi_p, \Psi_q) = \sum_{\forall q \in \Phi} [(I_r - I'_r)^2 + (I_g - I'_r)^2 + (I_b - I'_b)^2] \tag{15}$$

③To update confidence value of filled pixels:

$$C(p') = C(q), \forall p' \in \Psi_p \cap \Omega \tag{16}$$

To repeat the above steps until all of them are filled.

4.2.2 Improved Criminisi Algorithm

The isophote line vector of Criminisi algorithm is obtained based on calculating the gradient of RGB components, and making a simple addition, and finally orthogonalization. In fact, it is gradient value of grayscale image converted by color image. RGB model can't be well adapted to people's understanding for color because it is a linear representation system. Moreover, the Euclidean distance of two points in RGB space is not linear relationship with actual color distance, and it can cause the color not to be properly separated because of correlation between the three channels. All of them can influence the calculation of isophote line vector. Therefore, we propose to transform the multispectral image into the IHS color space which contains uncorrelated three channels, then calculate hue gradient, saturation gradient and gray gradient separately as image gradient values.

The conversion formula for RGB space to IHS space model is described in the literature[31]. Therefore, the gradient vector for the IHS image is defined as:

$$G_{IHS} = [x, y] = G_I + G_H + G_S \qquad (17)$$

Where G_I is grayscale gradient vector, G_H is chroma gradient vector, G_S is saturation gradient Vector.

The isophote line direction and the gradient direction of the point p is perpendicular, and modal values are equal to gradient values:

$$\nabla I^{\perp}_{p(IHS)} = [-y, x] \qquad (18)$$

Direction matching degree of point p is:

$$D(p) = \frac{\left|\nabla I^{\perp}_{p(IHS)} \times n_{p(IHS)}\right|}{\alpha} + \mu S(p) \qquad (19)$$

where $n_{p(IHS)}$ is the normal vector of damaged boundary, α is normalization faaactor and $S(p)$ is the sum of the standard differences of three independent components H、I and S, μ is normalization factor. The greater the sum of the standard deviation, the larger the color difference in the area where the p points are located and the more obvious the transition is. It states that it contains more structural information and should be given priority to inpaint the area.

The priority function still uses the function of the Criminisi algorithm: $P(p) = C(p).D(p)$

Criminisi texture inpainting algorithm which is based on isophote line searches for optimal matching blocks by traveling in the global image. It causes the operation time too long and is inefficient. According to the similarity of the image neighborhood, we can see that the best matching block of the filled block is within its neighborhood. Therefore, we can optimize the search range of the best similar matching block, and the search is performed only in the neighborhood of the current damaged area. Experiments show that the speed and inpainting quality have been improved after the improvement of search results.

5. Experimental Results and Analysis

5.1 Experimental Process

5.1.1 Multi-Channel Image Acquisition

According to the characteristics of Painting Arts, We use GTI Matcher standard lamp house, D50 light source and Nikon D7000 digital camera to support the experiment. By selecting the two filters with CCD sensor, we can obtain the image in three channel and obtain 6 images in total. Figure 1 shows the transmittance of spectral transmittance. Figure 2 shows the Multi-channel images.

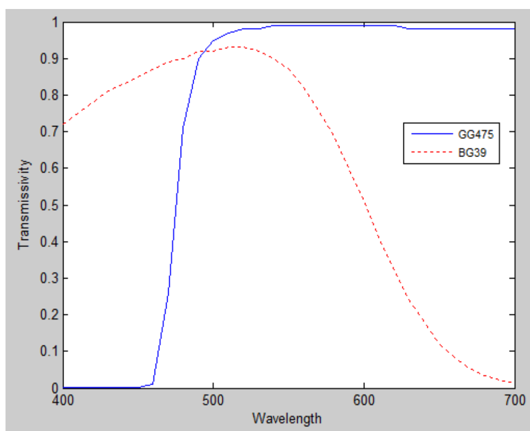
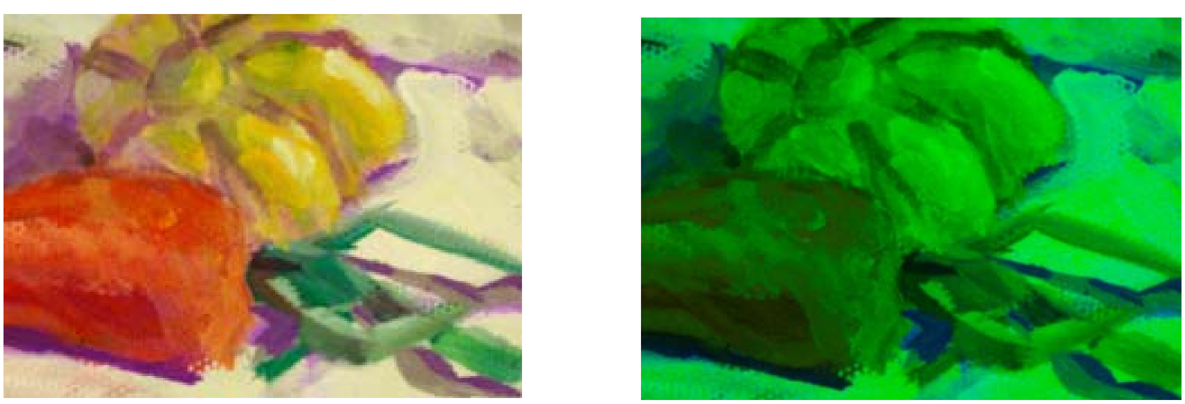


Figure 1. Transmissivity curves of BG 39 & GG475 bandpass filters



(a) Multichannel images obtained with GG475 filter

(b) Multi-channel images obtained with BG39 filer

Figure 2. The Multi-channel images of Printing Arts with Multispectral system

5.1.2 Spectral Reflectance Reconstruction and Color Reproduction

We select the color of Painting Arts to make 192 color blocks. Principal component analysis is carried out on the sample sets of homemade color cards. We can obtain the conversion matrix of Multi-channel image reconstruction, and then reconstruct the spectral reflectance of each pixel and achieve color reproduction of multispectral images based on formula (8). The result of multispectral image reconstruction is shown in Figure 3. We can see from Figure 3, the images of multispectral reconstruction have rich colors and clear details. It can meet the demand of digital collection and high fidelity replication of Painting Arts.

Figure 3. Multispectral image of reconstruction

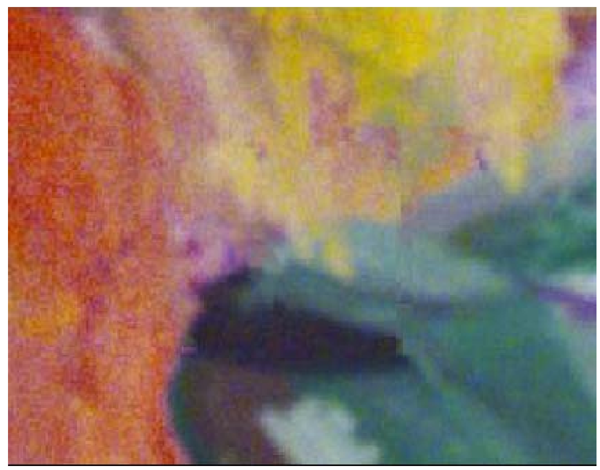
5.1.3 Multispectral Images Inpainting

Based on original image obtained, we inpaint color digital image virtually by the way of human destruction. As shown in Fig. 4 (a), reconstructed multispectral images are artificially destroyed, and as shown in Fig. 4 (b),multispectral images are inpainted based on improved Criminisi algorithm. Fig. 5 is a local image contrast between improved algorithm and original algorithm. Theimproved Criminisi algorithm is superior to the original algorithm in inpainting quality, the image sawtooth effect is obviously reduced, the quantities of pseudo color are reduced obviously, the image details, the image texture and structure are better.

(a) Multispectral damaged image

(b) Multispectral Repaired image

Figure 4. Damaged area inpainting results of multispectral image



(a) local image based on improved Criminisi algorithm

(b) local image based on Criminisi algorithm

Figure 5. Local image compare of Criminisi algorithm & Improved algorithm of multispectral image

5.2 Quality Evaluation of Inpainting and Result Analysis

It is difficult to be completely consistent between inpainted image and original image. There must be differences. The differences reflect the image inpainting quality. There are two methods to evaluate the image inpainting quality including subjective and objective separately. This experiment employed mean square error (MSE) and peak signal to noise ratio (PSNR) [32,33] to evaluate the effect of the image inpainting algorithm, and the subjective evaluation was used at the same time.

①Evaluation method of MSE

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[f_o(i,j) - f_R(i,j)]^2 \qquad (20)$$

MSE can be used to measure the deviation degree of two images. Under the condition of the known original image, When the MSE between the restored image and the original image is smaller, the restored image is closer to the original image, and the smaller the deviation degree is, the better the inpainting effect.

②Evaluation method of PSNR

$$PSNR = 10\lg\left(\frac{255^2}{MSE}\right) \qquad (21)$$

The PSNR is the ratio between the maximum signal value and the image noise value. The larger the PSNR value, the closer the inpainted image is to the original image, the less inpainted distortion is, the better inpainted effect.

	MSE	PSNR
General images inpainting with Criminisi algorithm	7.07133	8.9611
Multispectral images inpainting with Criminisi algorithm	5.8865	1.2648
Multispectral images inpainting with Shen	5.6274	41.3827
Multispectral images inpainting with Hareesh	5.4759	41.5726
Multispectral images inpainting with improved Criminisi algorithm	5.4021	41.6320

Table 1. MSE &PSNR of the inpainting multispectral image

It not only obtains color information accurately which is closer to the image inherent color and human eye observation effect, but also can record clear details based on improved Criminisi inpainting method of multispectral images from Fig. 4 and Fig. 5. It laid the foundation for the digital inpainting of damaged image. At the same time, we can obtain ideal inpainting image of texture and structure by improved Criminisi inpainting method, so that the quantities of pseudo color image are reduced obviously, detail distortion and sawtooth are reduced, the visual effect is better.

From table 1, for the general image, the MSE is higher and the PSNR is lower obviously, improved Criminisi algorithm achieves higher PSNR and lower MSE, and has less deviation degree to original image. Therefore, it can obtain higher inpainting quality because multispectral images have more vivid colors, transition boundary of image color is obvious, gradient is significant, and the priority of the inpainting block is higher. Shen inpainting results will still be blurred, and the Hareesh inpainting method is difficult to keep the structure coherence for damaged images with more texture information. Therefore, the results of MSE and PSNR are still not ideal.

6. Conclusion

In this paper digital image inpainting method based on multispectral image texture synthesis is proposed for damaged Painting Arts image. The principal component analysis method was used in multispectral images reflectance reconstruction. We obtain high quality of spectral image reconstruction by this method, color reproduction effect of multispectral images is better. The improved Criminisi algorithm was used in digital impainting of multispectral images, increased the inpainting quality of multispectral images, improved method is superior to general image inpainting and Shen and Hareesh inpainting methods, and obtained the inpainted images with rich colors, abundant details, less distortion and less pseudo color. It lays the foundation of reconstruction image color of multispectral images, and can provide reliable basis for digital inpainting and digital archive work of Painting Arts.

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