The Highly Lose Image Inpainting Method based on Human Vision

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Abstract

Currently, noise interference and data loss are two major problems that affect the processing results of image data transmission and storage. In order to restore damaged image data effectively, we propose a novel image inpainting technique based on wavelet transformation. The primary feature of our proposed technique is to separate the given image into two principal components which encompass image texture and color respectively. Then, according to the distinctive qualities of the given image, various image inpainting methods are adopted to perform image repair. By taking advantage of the separation of an image into its individual frequency components, we use the multi-resolution characteristics of wavelet transform, from the lowest spatial-frequency layer to the higher one, to analyze the image from global-area to local-area progressively. In order to substantiate the effectiveness of our proposed image inpainting method, we employed various images subject to high noise interference and/or extensive data loss or distortion. The experimental results were perfect, even if the distortion portions of the repaired images were higher than 90%.

1. Introduction

In the process of image transmission or storage, image data is subject to the noise interference and data loss. When the above mentioned disturbances occur at high level, they would be difficult to retain its original configuration, and the areas of repaired images would be easily distinguished and the repaired images would be far from the original ones. Nevertheless, the image inpainting technique has been in high demand by museums in order to repair damaged images as well as to store large amounts of image data. In order to effectively retain the image data, various researchers have continually proposed various methods of image inpainting [1-9]. These image inpainting methods can be divided into two forms of analysis, which can be viewed from two different perspectives: texture analysis and color analysis. In the texture analysis, the image inpainting technique considers spatial texture directly up to the related position used [1-4]. Conversely, in the color analysis, the color components of the original image are first converted into various domains through different color system transformations, and then depending on the diverse color composition trend analyses, the color components of damaged regions are repaired separately[5-9]. However, the above mentioned methods are unable to combine their respective advantages in the area of image inpainting in different analysis domains.

Taking account of the advantages of two previously mentioned techniques, we used discrete wavelet transform (DWT) to resolve Y component (texture) image into multiple layers so as to make the spatial frequency analysis possible. The wavelet coefficients of the converted textural image include simultaneous spatial-frequency relativity and produce multi-resolution layers with different frequency characteristics. By recognizing the concept of multi-resolution image inpainting, a proper image inpainting procedure shall be sequentially started from the lower layer to the higher layer. In Addition, the color components of the image (Cb and Cr) serve as a supplementary reference to support the linear interpolation method applied during damaged data prediction. This paper is organized as follows. In section 2, we briefly review the repaired information analysis. The proposed visual resolution inpainting algorithm is illustrated in section 3. In section 4, we evaluate the performance of various types of natural images. Finally, concluding remarks are given in section 5.

2. Overview

2.1. The Image Multi-resolution Analysis

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In wavelet transform, with respect to the spatial domain Vj+1, the function f(x) can be expressed as the base expansion of the layer 1 spatial domain, analyzed as the following equation (1):

$$f(x)=\sum_k c_{j,k}\phi_{j,k}(x)+\sum_{j=0}^{j} d_{j,k}\psi_{j,k}(x) \tag{1}$$

Where $\Phi_{j,k}$, $\Psi_{j,k}$ represents the scaling function and the wavelet function respectively, and satisfy the following two equations (2)&(3):

$$\phi_{j,k}(x)=2^{j/2}\phi(2^j x-k) \qquad j,k\in z \tag{2}$$

$$\psi_{j,k}(x)=2^{j/2}\psi_{j,k}(2^j x-k) \qquad j,k\in z \tag{3}$$

Where $c_{j,k}$ and $d_{j,k}$ represent the expansion coefficients of Vj and Wj spatial domains respectively, and can be evaluated by the following two equations:

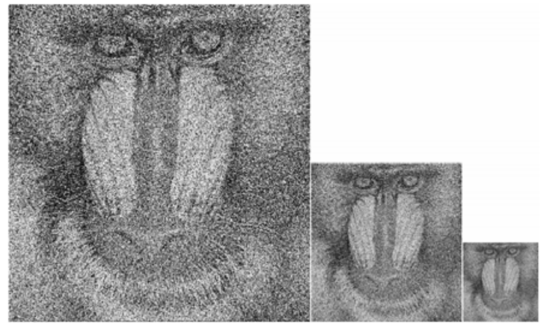
$$c_{j,k}=\sum_n c_{j+1,n}h(n-2k) \tag{4}$$

$$d_{j,k}=\sum_n c_{j+1,n}g(n-2k) \tag{5}$$

where h(n) and g(n) are called scaling coefficients and wavelet coefficients respectively. By observing equations (4) and (5), coefficient $c_{j,k}$ is evaluated based on the coefficients of $c_{j+1,k}$ from a prior layer in the spatial domain and the scaling coefficient h(n) after the execution of the folding evaluation and the decreasing of the sampling rate by 2. Similarly, coefficient $d_{j,k}$ is evaluated based on the coefficients of $c_{j+1,k}$ from a prior layer in spatial domains and the wavelet coefficient g(n) after the execution of the folding evaluation and the decreasing of the sampling rate by 2. This is the reason that wavelet transform and the wave-filtering theory are capable of being combined [11].

2.2. The Visual Analysis Method in Destroyed Image

The losing information of the image can be divided into two kinds of conditions. In the first condition, the distribution of the losing information of the image is the local and concentration. The decision method of the image inpainting depends on the characteristic and direction of the neighboring textures. In the other one, the distribution of the image losing part is global and dispersion. Therefore, when the image lost a great deal, we can't clearly repair the destroyed image through neighborhood. To solve this problem, we imitate the artistic techniques to approach the effectiveness of image inpainting in human vision. We take account of the multi-resolution characteristics of wavelet transform, from the lowest spatial-frequency layer to the higher one, to analyze the image from global-area to local-area progressively. If the destroyed images lack of reference data to repair, we zoom out them to search the image shape and utilize the down-sampling method to reach the visual effect. Fig. 1 shows the down-sampling image.



(a) (b) (c)

Fig.1 Down-sampling image (a)Original size (b) One time down-sampling (c) Two times down-sampling

3. Visual resolution inpainting

The idea of the color image will be been divided into the color component and the texture component. We know the significance of the texture component (Y) on the color image reconstruction. And in order to acquire the vision concept in the 2.2 section, we use the n-level wavelet transform to separate the texturing image (Y) into different frequency components. We acquire the multi-layer of the different frequency composition of the texture image by the wavelet transform. But the amount of the losing pixels is different, so we handle the repair of the texturing image on the different frequency layer. If we repair the few amount of the losing pixels at the low frequency layer, the originally existent pixels will lose and the image quality that should reserved would be deteriorate clearly. Besides if we repair the grand amount of the losing pixels at the high frequency layer, the low frequency composition of the image shape will be repaired by the mistake. According to this concept, the repairing method must to decide the initial layer of the repairing pixel. When the layer number n be reduce by one which mean carrying out the 1-level inverse discrete wavelet transform, the layer exists its relative subband LL_n. We must to calculate the relative amount of the valid pixels of the original image that per pixel be included in the LL_n. If the any pixel exists in the LL layer which relative the amount of the valid pixels is to satisfy the follow equation (6), and the pixel in the LL_n will start being repaired in this layer.

$$N_{vp,n}(i,j) = 2^n \times 2^n \tag{6}$$

Where $N_{vp,n}$ is the total number of the valid pixel in the layer n. In another condition, $N_{vp,n}(i,j) < 2^n \times 2^n$, the repair procedure of the pixel(i,j) will not carry out under the layer n. But the opposite pixel of the pixel (i,j) will be checked whether handle the repair procedure after the next layer by the IDWT. The repair method reconstructs the damage image gradually from low frequency component to high frequency component. When the repair procedure arrives at the highest frequency layer in the wavelet domain, we will acquire the reconstruction image of the highest resolution.

Besides, we will make use of the color composition of the image that have the regional characteristic. For repair the local District of the color image availably, we proposed the repair method aim at in the image of grand losing rate which based on the two dimensions linear interpolation. We must consider the condition which in the grand losing rate, the image data consulted will become limited. So we aim the traditional linear interpolation method to take modification. Because we have no way assurance that the physically and the effectively pixel information exist on the nearest neighbor position.

In proposed repair method, we define the different the weighting values that consider the relating distance from the repair target T, as shown in the Fig. 2.

0.5	0.5	0.5	0.5	0.5
0.5	1	1	1	0.5
0.5	1	T	1	0.5
0.5	1	1	1	0.5
0.5	0.5	0.5	0.5	0.5

Fig.2 The related weighting value of the different distance

If the most neighboring district exist more than two reference pixel value, we will only consider the most neighboring district pixel value to repair image. But if the reference pixel is not exists anyone or just only one, we must extensive the distance of the consideration.

4. Experimental Results

In order to test the quality of our proposed image inpainting method, we used various images, including photos, scenery, and artistic compositions as testing

Fig.3 Experimental results for the different test images:(a)Lena: (a-1)Noise ratio=61.2%, (a-2)PSNR=32.16dB(b)Girls: (b-1)Noise Ratio= 73.1% (b-2)PSNR=36.13dB (c)Gold Hill: (c-1) Noise ratio=80.6%, (c-2)PSNR=31.19dB (d) Pepper: (d-1) Noise ratio=90.3%, (d-2)PSNR= 26.13dB

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subjects and adopted various noise interference intensities to observe the variation of image inpainting results. We have selected four test images that are the most commonly used in the field of image restoration research and processed them through our proposed image inpainting method. The results of the image inpainting effectively restore the image textures observed by the highly losing rate of the damage image, as illustrated in Fig. 3. Alternatively, Fig. 4 illustrates the four image inpainting results generated through various signal to noise interference ratios. We can clearly observe that our proposed algorithm successfully restores an image even when the image is under the influence of 90.3% noise interference.

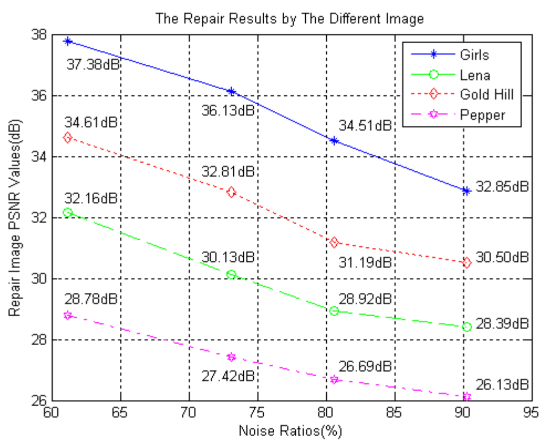

Fig.4 Comparison of the repaired results for the different test images with various noise ratios.

5. Conclusions

Our proposed method could successfully resolve high image vein defections which simple color image restoration methods would be unable to process. Empirically, the results generated by our proposed method clearly illustrates superior image inpainting that other present image inpainting methods and techniques are unable to achieve. In the future, we will strive to modify the repair method in the color components of Cb and Cr of an image using wavelet transformation as our working foundation in order to achieve even more superior image inpainting results.

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