The Visual Image Inpainging Method apply to the Highly Lose Image

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Abstract: - Noise interference and data loss are two major problems that affect the processing results of image data transmission and storage. In order to effectively restore damaged image data, we propose a new image restoration technique based on wavelet transformation analysis. The primary feature of our proposed technique is to initially separate the given image into two principal components which encompass image veins and image color, respectfully. 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, a characteristic unique to wavelet transformation, our proposed method processes an image sequentially from the lower frequency layers of an image to the higher frequency layers. 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 results were extremely satisfying, even to the extent that the repaired images for distortion to over 90% show little or no indication that the image was once damaged.

Key-Words: Image Iinpainting, Wavelet Ttransform, Multi-Resolution, Imitate the Artistic Technique and Progressive Processing.

1 Introduction

In the process of image transmission or storage, image data is subject to the influence by noise interference and data loss. When the above mentioned disturbances occur at high level, it would be difficult for the given image to retain its original configuration, and if the repair is ever started, the areas of repair would be easily distinguished and the resulting image would be far from the original one. Nevertheless, 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 [eg.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 compositions 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.

By taking into account the advantages of two previously mentioned techniques, we used discrete wavelet transform (DWT) to resolve Y composition (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. The pepair information analysis is illustrated in section 2. 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 The Repair Information Analysis

From the perspective of human vision, the image inpainting process involves three primary areas of concern: the image multi-resolution analysis, the color analysis, and Visual Analysis Method in Destroyed Image. Similarly, during an artist's process of repairing an artifact, visual perceptions will move from global-area to local-area progressively. In order to resolve the above-mentioned obstacles, we utilize the multi-resolution characteristics within various spatial domains of WT, predict the inpainting trend in each resolution layer and preserve the overall composition as well as the reconstruction of high-frequency textures. In order to accomplish the results of inpainting for both global-area and local-area, we have to take account of the information in different frequency bands. When determining the outline of an image, it would not desire to be influenced by complicated high frequency components. On the contrary, as the resolution increases, the high frequency components become more important for image inpainting. For these reasons, we utilize the multi-resolution characteristics of WT for image inpainting.

2.1 The Image Multi-resolution Analysis

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 Φj,k, Ψj,k represents the scaling function and the wavelet function respectively, and satisfy the following two equations (2)&(3):

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

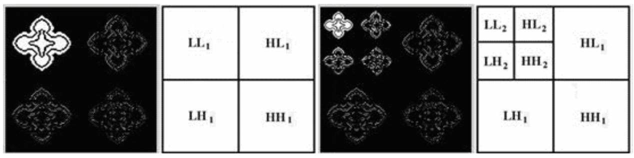
$$\psi_{j,k}(x) = 2^{j/2}\psi_{j,k}(2^j x - k) \qquad j,k \in z \tag{3}$$

Where cj,k and dj,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 cj,k is evaluated based on the coefficients of cj+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 dj,k is evaluated based on the coefficients of cj+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].



(a) (b) (c) (d)

Fig. 1 Results of the wavelet transformation analysis derived from various layers of a given image (a) 1-Level DWT image (b) 1-Level DWT Resolution (c) 2-Level DWT image (d) 2-Level DWT Resolution

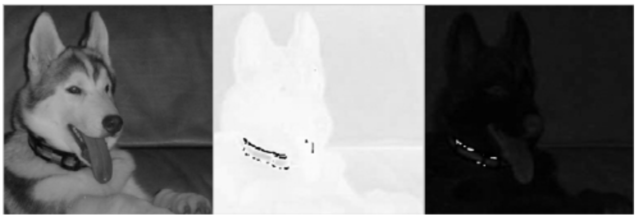
The original image was processed through a secondary-level wavelet transformation analysis, as illustrated in Fig. 1(c), where the highlighted image in the uppermost left hand corner is represented by the section LL2 illustrated in Fig. 1(d). Where analysis is concerned, the components of the overall image composition are all taken into consideration. This procedure can also be utilized as preliminary image analysis. The four components LL2, LH2, LH2, and HH2 are then processed through reversed wavelet transformations to heighten the resolution of the image. As shown in Fig. 1(a), where the highlighted image in the upper left hand corner is represented by the section LL1 illustrated in Fig. 1(b). This would result in the increasing of frequency components within the image, which would then contribute towards the depiction of local area textural features.

2.2 The Color Analysis

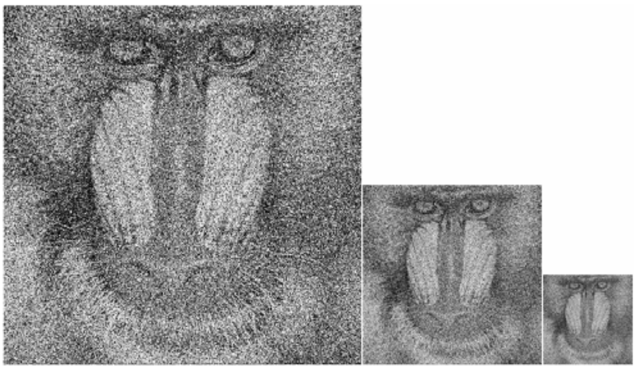
In the image in order to separate the texture composition and color composition, we have to use the color conversion formula to the process. Among them, the texture composition is importance than the color composition. for example DVD compression format (4:2:2 or 4:1:1), we can know the importance of finding the texture. The color conversion formula is as follows:

$$Y = 0.299 * R + 0.587 * G + 0.114 * B \quad (6)$$
$$Cb = -0.169 * R - 0.331 * G + 0.555 * B \quad (7)$$
$$Cr = 0.500 * R - 0.419 * G - 0.081 * B \quad (8)$$

We use concept which the high district relation of the colorful composition and the texture composition is whole area relation. So we can carry out the different image repair method respectively on the different image composition. In the repair of the texture composition carry out the global analysis and fine repair method. Relatively, in the repair of the color composition carry out the local similar repair method. In Fig.2, we can clearly see the texture and color characteristic.



(a) (b) (c)
Fig.2 Image characteristic:
(a)Texture composition (Y) (b)Color composition (Cb) (c)Color composition (Cr)



(a) (b) (c)
Fig.3 Down-sampling image (a)Original size (b)One time down-sampling (c) Two times down-sampling

2.3 The Visual Analysis Method in Destroyed Image

The losing information of the image can be divided into two kinds of conditions. The first class, the distribution of the losing information of the image is the local and concentration. So the decision method of the image repair can depend on the characteristic and direction of the neighboring textures to decide. The second class, the distribute of the image losing part is global and dispersion. Therefore when the data a great deal of creation lost, we can't clearly repair the repair image through the consult data of the neighboring district. For to solves the problem, our use the mankind's vision characteristic which make the basis of the repair. When the reference data shortage to repair the image, we zoom-out the distorting image can observe the image shape. Actually in the image processing, we use the down-sampling method to reach the visual effect, as illustrated in Fig. 3.

3 VISUAL RESOLUTION INPAINT -ING

In this section, we will be detailed to introduce the image repair algorithm that we proposed. In 3.1 section, we introduce the flow chart of the visual resolution inpainting (VRI). Further to introduce the detailed repair method in the different image composition respectively. The idea described according to forward section, our repair image method divided into two kinds of dissimilarity repair methods of the texture composition and colorful composition. The main reason which we handle image separately, these two kinds of image compositions have the different characteristic. These two kinds of different methods will be detailed in section 3.2 and section 3.3.

3.1 The Flow Chart of Visual Resolution Inpainting (VRI)

The idea described according to the 2.2 section, the damaged of the color image will be been divided into the color composition and the texture composition. In fig 2(a), we can find the importance of the texture composition in color image reconstruction. And using the vision concept in the 2.3 section, we use n level wavelet transform to separate the texture image (Y) into different frequency compositions. The method repaired the distortion image from the low frequency composition repair to high frequency composition repair gradually. When we repair to the highest frequency layer in the wavelet domain, we will acquire the reconstruction image of the highest resolution. Besides in fig. 2(b) and 2(c), we can obviously find the color composition, Cb and Cr, has the highly neighboring relativity. So we only need to use the neighboring information of the valid to repair the color image. According to the concept, we have to put the reference target on the neighboring district. So we choose the linear interpolation to be used as the repair method in the color distortion image.

Finally, we acquire the repaired image by the YCbCr to RGB conversion through use the two repaired image composition. The flow chart of the visual resolution inpainting is shown in Fig.4. The texture composition image repair method and the color composition image repair method will be discussed in section 3.2 and sections 3.3 separately.

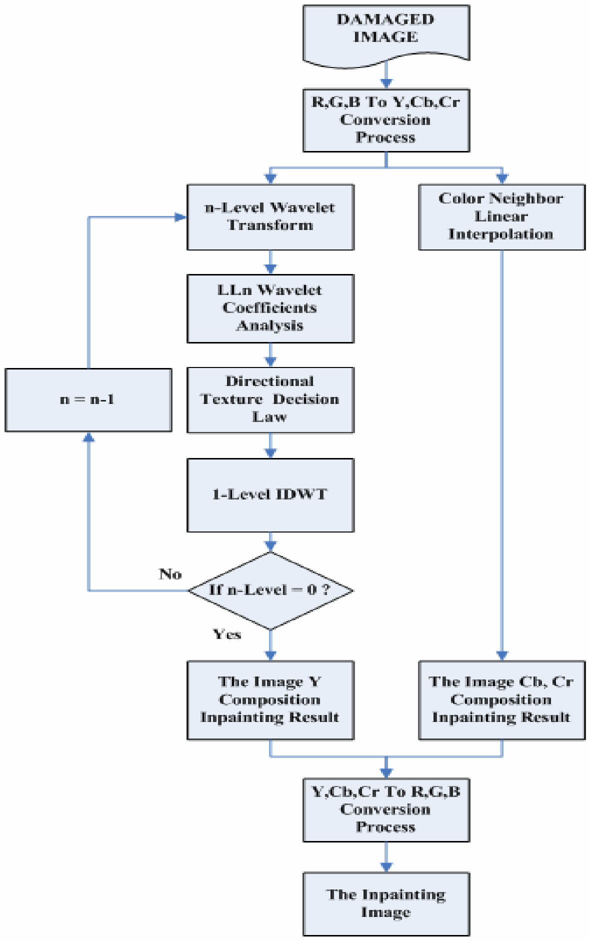


Fig.4 Flowchart of the proposed visual resolution inpainting algorithm

3.2 The Image Repairing Method in Texture Composition

In the human's vision, the texture composition of the color image has the important contribution. For repair the texture composition, we proposed the global and the multi-frequency method to reconstruct the image. The repair method established on the wavelet domain characteristic of the space-frequency relativity. Thus, we analyze the multi-layers of the image which through the wavelet transform. From the low frequency layer to the high frequency layer to reconstruct the image, we will acquire the precise repairing image.

First, 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 (IDWT), 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 (9), and the pixel in the LL_n will start being repaired in this layer.

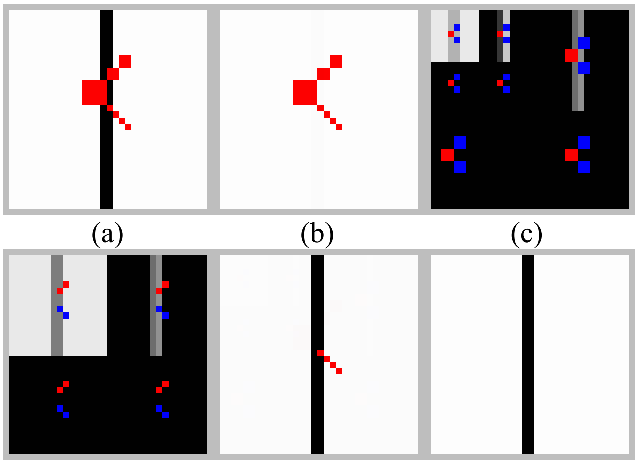
$$N_{vp,n}(i,j) = 2^n \times 2^n \tag{9}$$

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. In the fig. 5, we use the different size of the damage block to explain which damage block should be repaired in which layer. The image include the different sizes of the damage block (4x4, 2x2, and 1x1), shown as the fig. 5(b). The image through 2-level wavelet transform that only an damage block need to repair, shown in the red mark of the fig. 5(c). And the block of the red mask will be repaired in the current layer. By the 1 level of the IDWT, the new repair area will be decided in the LL1, shown as the fig. 5(d). Finally, the damage block of the 1x1 size will be repaired in the original image size, shown as the fig. 5(e).
If we decided the initial repair in which layer, after we must to decide how to repair the image. So we according to the characteristic of the tree structure of the wavelet domain to decide the repairing coefficients, shown as the fig. 6. The tree structure includes the different repairing method of the four

components (Mean, Vertical Branch, Horizontal Branch and Diagonal Branch). According to separate the idea of the repair, we consider the pixel value of the different direction to handle the repair procedure. The repair of the MEAN composition influence the shapes of the object therefore us consider the whole of the bigger area, shown as the Fig. 7.(a). Besides, the repair method of the directional branch will consider its corresponding directional reference coefficient, shown as the Fig. 7(b)-(d).
The best similar pixel search which using calculate the energy of the differential pixel by the following equation (10):

$$DE = \sum_{\forall i}\sum_{\forall j}[d(i,j) - s(\Delta i + i, \Delta j + j)]^2 \qquad (10)$$

Where DE is the differential energy between the damage image and the search image. The different repair method want to calculate the DE value must consider the valid pixel of the different direction, shown as the Fig. 7.



(d) (e) (f)

Fig.5 Inpainting a damaged image by utilizing the different wavelet transformation layers (a)The damaged image (b)The MASK region with red blocks (c)The repaired red block of Level-2 DWT (d)The repaired red block of Level-1 DWT (e)The repaired red block of original domain (f)The inpainting image.

3.3 The Image Repairing Method in Color Composition

According to the concept of in the 2.3 section, 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. 8.

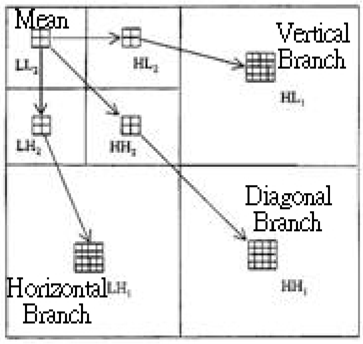
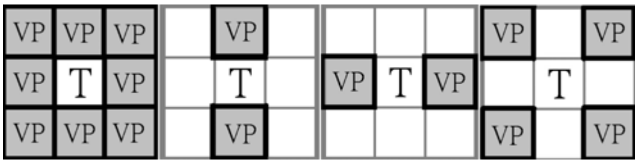


Fig. 6 The "tree structure" correlation of wavelet transformation



(a) (b) (c) (d)

Fig.7 the directional valid pixel (VP): (a)Mean (b)Vertical (c)Horizontal (d) Diagonal

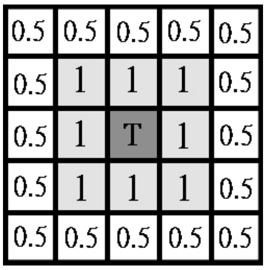


Fig.8 The related weighting value of the different distance

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. Using this concept, we proposed the revised method of the linear interpolation for the color restoration repair method. The new linear interpolation function as the following equation (11) & (12):

$$w_{total} = \sum_{\forall i} \sum_{\forall j} w_{ij} \quad , if \;\; pv(i, j) \; is \; valid \qquad (11)$$

$$C_{new} = \frac{1}{w_{total}} \sum_{\forall i} \sum_{\forall j} w_{ij} * C_{ij} \qquad (12)$$

Where $pv(i, j)$ is the valid pixel value of the image, w_{ij} is the weighting value on (i,j), w_{total} is the total weighting value of valid pixel value, C_{ij} is the valid pixel value and C_{new} is repair pixel value on the target T. The w_{total} be calculated for normalize the repair value of the linear interpolation pixels, in function (12).

4 Experimental Results

In experimenting result, we try the different experiment to prove the superiority of proposed method. Two major experimental processes are conducted: Section 4.1 shows a comparison of image inpainting results among various current inpainting methods. Section 4.2 We use the several different characteristic of the images, prove the our repair method be used widely. We use the several images of the different characteristics, prove our repair method be used in the different image repaired widely.

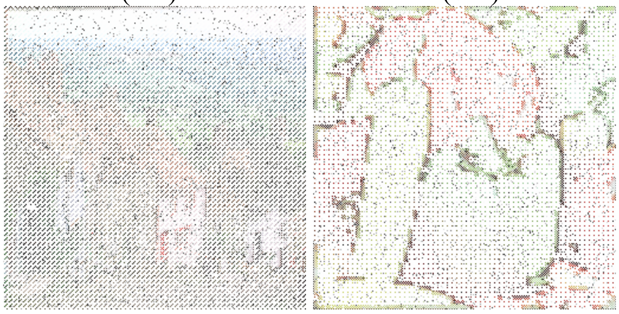
4.1 A comparison of image inpainting results among current inpainting method

First, For prove our image repair method on the highly losing rate image acquire the better repair result than the current image repair method. We comparing our results with shih's image inpainting method [9], we can clearly see that our proposed algorithm generates results that are more enhanced than that of the Shih's method, as illustrated in Table 1.

Table 1 PSNR values of image with different inpainting methods

Figures	Noise ratios	PSNR values (dB) of the repair image	
		Our method	Shih's Method [8]
Lena	61.2 %	32.16	30.10
Girl	73.1 %	36.12	28.16
Gold Hill	80.6 %	31.19	30.90
Pepper	90.3 %	26.13	22.10

(a-1) (b-1)



(c-1) (d-1)

(a-2) (b-2)

(c-2) (d-2)

Fig.9 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)Ppepper: (d-1) Noise ratio=90.3%, (d-2)PSNR=26.13dB

4.2 The results of utilizing the image inpainting algorithm on different images

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

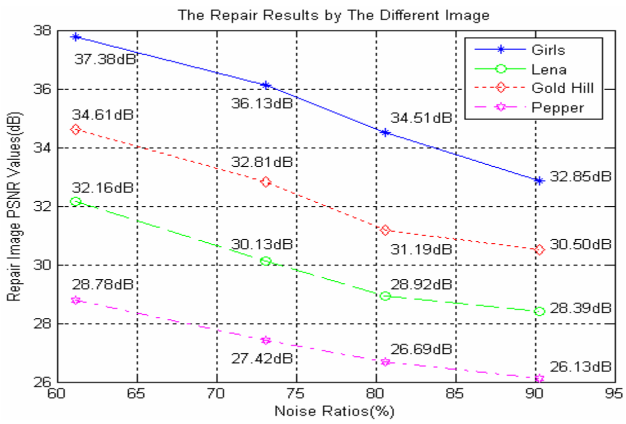


Fig.10 Comparison of the repaired results for the different test images with various noise ratios.

5 Conclusions

In this paper, we propose a new image inpainting technique that emphasizes image textures and color components. By taking advantage of the characteristics unique to the image veins and color, the image repair procedure can be determined individually. Since the Y component is the primary factor of a color image, this paper focuses on the reconstruction procedure of the Y component. By utilizing the multi-layer wavelet transformation analysis, a sequential image restoration process can be generated and performed on various layers of the image, while 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.

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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