Fast Image Restoration using the Multi-Layer Best Neighborhood Matching Approach

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Abstract: - This paper presents an accurate and fast image restoration for lost block images via wireless image transmission. In the network transmission of block-coded images, fading in wireless channels and congestion in packet switched networks could cause entire blocks to be lost. Instead of using retransmission query protocols, we reconstruct the lost block on the wavelet domain that considers the relation between the lost block and its neighbor coefficients. Thus, this method could use the transmitted image immediately and increase the transmission rate of the network bandwidth. The algorithm considers both the best neighborhood matching (BNM) and the different frequency contents of the multi-layer on wavelet domain, which is referred as the Multi-Layer Best Neighborhood Matching (MLBNM). The MLBNM is proposed to improve the efficiency of search processing and to reconstruct the different frequency composition separately. This method considers the different veins of the directional composition and the independent directional estimation, so that the veins will not influence each other. The experimental results demonstrate the high restoration quality of the proposed system.

Key-Words: Wavelet, Image Restoration, Wireless, BNM and MLBNM.

1 Introduction

In order to reduce data size, many compression methods (e.g. for document files, image files etc.) are proposed. In the image compression standard, common operations like JEPG or JPEG2000 [1] encoder tiles the image into blocks of $n\times n$ （8x8 or 16x16）pixels, calculates a 2-D transform, quantizes the transform coefficients and encodes them using Huffman or arithmetic coding. Variable length coding is usually used in a block-based coding system. Thus, the encoded bit stream can easily be damaged on the transmission. When a single bit of the transmission stream is lost, the results carry through to the loss of a whole block to even cause consecutive block losses. The common techniques to recover lost blocks are grouped under Automatic Retransmission Query (ARQ). As previously noted [2], ARQ will reduce data transmission rates that can further increase the network congestion and aggravate packet loss. Under the limited bandwidth of wireless networks, these conditions will be more obvious. Average packet loss rate in a wireless environment has been shown to be 3.6%, occurring in a bursty fashion [3]. Therefore, the reconstruction of lost blocks on the transmission has been broadly studied by researchers in the past several years.

In the image restoration algorithm, the block repair method is to carry out on the spatial correlation property of the natural image. The interpolation method uses those belonging to the surrounding blocks to interpolate the missing dc and the lowest frequency ac [4],[5]. Zhang et al. proposed the BNM and JLBNM that are based on the block-wise similarity with a natural image to carry out the reconstruction [6],[7]. With regard to the information used for restoring damaged blocks, error concealment algorithm by block- wise similarity can be categorized into two frameworks: the local correction framework [4],[5] and the long-range correlation framework [6]-[8]. The BNM and JLBNM are based on the idea of the existence of abundant long-range correlations within natural images. The main reason is what the long-range correlation image restoration is able to utilize not only the information of neighboring pixels, but also correlation information among remote regions in the image.

In this paper, In order to obtain fast and correct construction of lost blocks, we here propose a novel block reconstruction method that considers both the BNM and the characteristic of wavelet transform [11],[12], called the Multi-Layer Best Neighborhood Matching (MLBNM). This paper is organized as follows. In section 2, we briefly review two main problems related to image inpainting, and including wavelet transform, BNM. The details of the MLBNM are presented in section 3. In section 4, we compare its performance with the best existing methods and various types of natural images. Finally, concluding remarks are given in section 5.

2 Previous Related Work

In order to acquire good repair results, the damaged block reconstruction needs to address two primary areas of concern: the analysis domain of the damaged image, and the block repairing reference data. In order to obtain faster and better repair results, we utilize the multi-layer concept of wavelet transform to carry out image decomposition. By this method, a complicated image will be decomposed according to the veins composition of the different frequenciesy and different directions to help repair the image.

2.1 Discrete Wavelet Transform

In wavelet transform[12], 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):

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

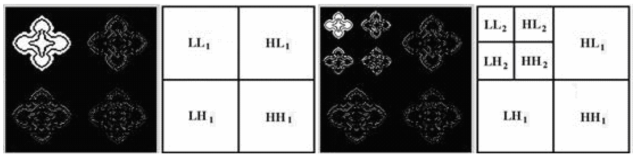
$$\psi_{j,k}(x) = 2^{j/2}\psi_{j,k}(2^{j}x - k) \quad j,k \in z \tag{3}$$

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 BNM

To search for the best similar image block to repair a damaged image, Zhang [6],[7] proposed two different repair algorithms includes the Best Neighborhood Matching (BNM) and the Jump and Look around BNM (JLBNM). The main concept of these methods is considers information surronding the damaged block $x_{i+m,j+n}$ by one pixel width. Moreover, these methods use neighborhood pixel information through the 1-order matching function $v(z)$, as Eq. (6), to transform that will compare with the same size blocks within the searching range block. Through constant comparison, the best neighborhood matching block will obtain the minimum MSE_M by Eq. (7) .

$$v(x) = a_0 + a_1 x \tag{6}$$

$$a_1 = \frac{n_M \cdot \sum m \cdot x_d \cdot x_r - \sum m \cdot x_d - \sum m \cdot x_r}{n_M \cdot \sum m \cdot x_r^2 - \left(\sum m \cdot x_r\right)^2}$$

$$a_0 = \frac{1}{n_M}\left[\sum m \cdot x_d - a_1 \cdot \sum m \cdot x_r\right]$$

$$MSE_M = \frac{1}{n_M}\sum_{m=0}^{N-1}\sum_{n=0}^{N-1}(1 - f_{k+m,l+n}) \cdot \left(v(x_{i+m,j+n}) - x_{k+m,l+m}\right) \tag{7}$$

$$m = 1 - f_{k+m,l+n}$$
$$x_d = x_{k+m,j+n}$$
$$x_r = x_{i+m,j+n}$$

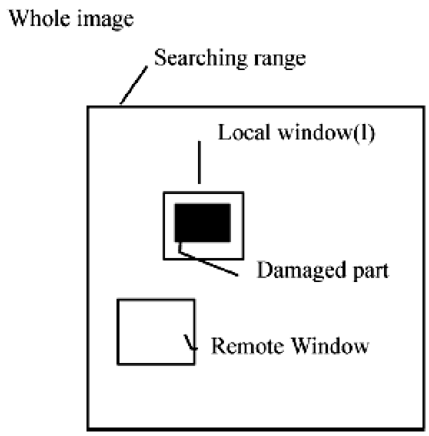
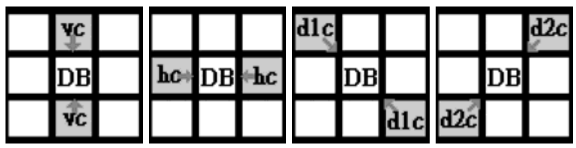


Fig. 2 Structure of lost block, range block, domain block, and searching block with their default sizes.

Where $v(x)$ is the 1-order matching function used to convert the neighboring information of the damage block x_d, a_1 is first order conversion coefficient of the 1-order matching function, a_0 is the zeroth order conversion coefficient of the 1-order matching function, x_r is the range block on the searching range block, x_d is the neighborhood information of the damaged block, and m is mark of the useful pixel value, the relation of the block matching method is shown in fig. 2. Although this algorithm can to find the best neighborhood matching block, this way requires high computation overhead to search for similar blocks. The JLBNM algorithm is for solving the problem of great computation overhead due to using the jump and look around method for reducing the searching range. However, this way will sacrifice the quality of the reconstructed image in exchange for lower computational overhead. In order to resolve this problem, we propose a new BNM algorithm that considers both low computation overhead and high repair quality. Its main idea is to search the best neighborhood matching from the eight neighboring blocks on the wavelet domain.

3 Proposed Algorithm

According to the results of the two major steps of the previous related work discussed above, this section concentrates on the integration of these steps and proposes an Multi-Layer Best Neighborhood Matching (MLBNM), to consider the different frequency composition and the different direction composition at the same time to carry out the image reconstruction.



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

Fig.3 The relation of each directional neighboring coefficient to repair the damaged coefficients on the damaged block: (a)Vertical (b)Horizontal (c)Left-top diagonal (d)Right-top diagonal

In this section, the proposed method uses the wavelet characteristic has multi-frequency bands to carry out the frequency composition repair on different frequency layers separately. The main idea of the repair image on the wavelet domain is from the method of Shantanu [10]. But its algorithm, in addition to handling complexity (classify) and in the wavelet coefficients decision, includes the two conditions for mistake repair and insufficient information. This proposed method is to resolve the complicated classification problem of lost blocks, and it uses the weight value of the neighborhood wavelet coe- fficients to replace the lost block classification. According to the different wavelet layers, we depend on the wavelet coefficients of the different layers multiplied by the different weight value, and thus refer to it as the directional wavelet weight method (DWWM). This formula is shown as Eq. (8)-(12) and the relations of each layer multiply the weight value to repair the area shown in Fig. 3.

$$vwv = 4 \times abs(vc_2) + 2 \times abs(vc_1) + 1 \times abs(vc_0) \tag{8}$$

$$hwv = 4 \times abs(hc_2) + 2 \times abs(hc_1) + 1 \times abs(hc_0) \tag{9}$$

$$d1wv = 4 \times abs(d1c_2) + 2 \times abs(d1c_1) + 1 \times abs(d1c_0) \tag{10}$$

$$d2wv = 4 \times abs(d2c_2) + 2 \times abs(d2c_1) + 1 \times abs(d2c_0) \quad (11)$$

$$twv = vwv + hwv + d1wv + d2wv \quad (12)$$

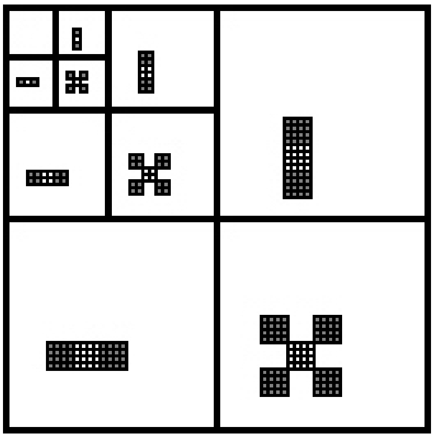
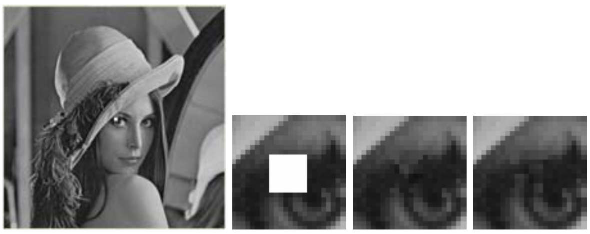


Fig. 4 The related position of the directive veins coefficient in wavelet resolution layer.

Where vwv, hwv, $d1wv$, and $d2wv$ are the absolute weight values of the neighborhood block of the vertical, horizontal, left-top diagonal, and right-top diagonal separately; hc_n, vc_n, $d1c_n$, and $d2c_n$ are the coefficients value of the neighborhood block of the vertical, horizontal, left-top diagonal, and right-top diagonal separately; and twv is the total weight value. The related position of these coefficients is shown in Fig. 4.

When the repair needs to obtain the contribution of the directional vein compositions, the significance of the four directional wavelet coefficients are calculated via each directional weight value to divide the total weight value (twv) separately that are the weight value. If this method did not consider these proportions of the directive information, the repaired image would have vein mistakes, as shown in Fig. 5. In Fig.5(c), we can clearly find two problems that includes around eyes is not continuously and the eyeball is out of shape.



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

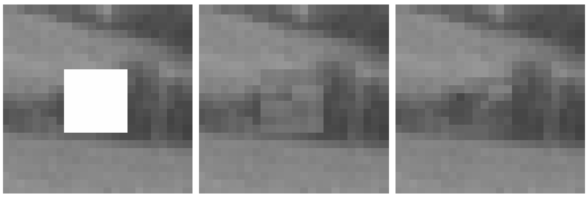
Fig. 5 Compare the repair results of consider these proportion of the directional information: (a)Damaged image (b)Zoom-in damaged area (c)Direct method (d)Consider directional weight value.

After predicting the wavelet veins for different directional information, although this method can acquire the vein images through the inverse wavelet transform, the repaired image will probably lead to the block effect, as shown in Fig. 6(b). In order to resolve this problem, we propose the adjustable block consecution method that is based on the concept that continuous blocks have the same pixel values. The main idea for this comes from the fractal geometry concept of searching for similar blocks to carry out the image compression. The adjustable block equation is shown in Eq. (13) and the estimate equation for the best neighborhood matching is shown in Eq. (14).

$$v(x_r) = g \cdot x_r + s \quad (13)$$

$$MSE_M = \sum (x_n - v(x_r))^2 \quad (14)$$

Where $v(x_r)$ is the adjusted block through the pixel value shift and the gradient adjustment and x_n is the neighboring pixels of the adjusted block. When the equation acquires the minimum value, it means the adjusted block obtains the best adjustment to connect the neighborhood blocks, as shown in Fig. 6(c). Through the adjustment method, the repaired image can avoid visual discomfort.



(a) (b) (c)

Fig. 6 The visual adjustment to solve the block effect of the reconstructed image: (a)Damaged block (b)not adjustment (c)Adjustment

4 Experimental Results

To demonstrate that the proposed method provides the most effective repair results, the major experimental processes were conducted. The results show a comparison of image repair results with the existing Shantau’s method, BNM and JLBNM methods.

In wireless transmission, the image is divided into blocks for transmission over a wireless channel. To consider different conditions, we have assumed that (1) the damage image includes the lost block and (2) continuous lost blocks (lines losses) that conform to the JPEG compression standard. In experiment, we consider only damaged block condition to carry out the repair test. The random block loss rates are arranged from 2.5% to 15%. These experimental results are separated into two groups. In the first group, repair results from the proposed method are compared with those from the existing the Shantanu' method, BNM and JLBNM methods for different block loss rates. We used the four testing images that are widely be used in image processing: the Lean, and the Goldhill. In Fig. 7, the repair results clearly show that the proposed method has higher PSNR and the good visual result than the existing method. The main reason for this is that is our method not only considers more reference information carried on the image repair estimate, but also considers the multi-directional veins extension. These restoration results using the different images via the different repair method are compared separately in Figs. 8 and 9.

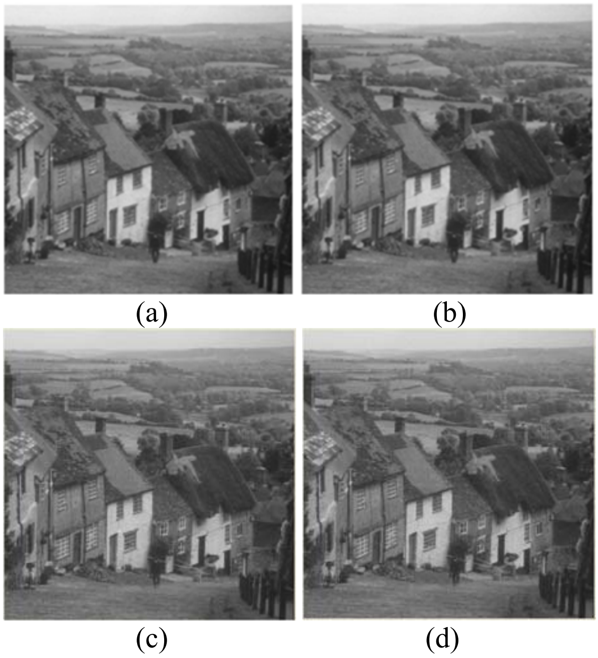


Fig. 7 The reconstructed results for “Goldhill” with block loss rate 10%. Block size is 8 x 8. (a)Restored image by BNM, PSNR=35.28 (b)Restored image by JLBNM, PSNR= 34.83 (c)Restored image by Shantau’s method, PSNR=35.68 (d) Restored image by MLBNM, PSNR=35.91

5 Conclusions

A novel algorithm based on the wavelet transform to reconstruct the block lost image was presented. This method is combined with the best neighborhood matching approach and the different-frequency repair on wavelet domain to carry on the fast lost block reconstruction. Thus, the inpainting image is divided into the different wavelet layers to carry out texture

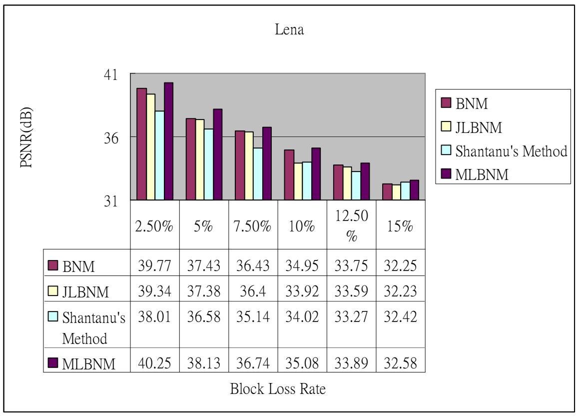


Fig. 8 Comparison repair results of the PSNR for “Lena” achieved by BNM, JBNM, Shantanu’s method and MLBNM.

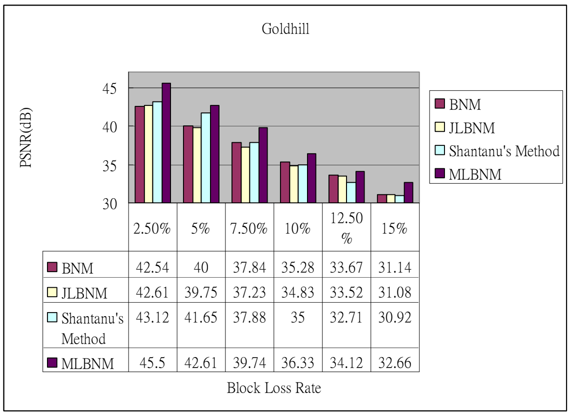


Fig. 9 Comparison repair results of the PSNR for “Goldhill” achieved by BNM, JBNM, Shantanu’s, method and MLBNM.

reconstruction and acquire the estimate of the best veins. The experimental results indicate that this algorithm provides significant improvement over existing algorithms in terms of both subjective and objective evaluations. The method considers the relationship between the different frequency compositions and each layer of neighboring texture at the same time. However, it does not need to use a long-range correlation to find the best neighborhood matching in the big search domain, because it will spend a lot of calculation time. Another significant advantage of method is that the image wavelet dimension not only resolves the different frequency compositions but also provides three directive compositions. Therefore, it is advantageous to repair the fast and right veins through the MLBNM algorithm.

Although the MLBNM provides better repair result than the existing BNM and JLBNM, its image repairing result still did not attain perfectly by simple directive estimation method. In future research, we will try to determine the better estimation method of directive veins to improve the repairing quality of the damage image.

Acknowledgements

The research is supported by National Science Council, Taiwan, at the contract number NSC 95-2221-E-032-046.

References:

[1] A.N.Skodras, C. Christopoulos, and T. Ebrahimi, "Jpeg 2000: The upcoming still image compression standard," Proceedings of the 11th Portuguese Conference on Pattern Recognition, Porto, Portugal, pp. 359–366, May 2000.

[2] S. S. Hemami, "Digital image coding for robust multimedia transmission," in Symposium on Multimedia Communications and Video Coding, (New York, NY), 1995.

[3] E. Chang, "An image coding and reconstruction scheme for mobile computing," in Proc. 5th IDMS, Oslo, Norway, Sept. 1998, pp. 137–148.

[4] X. Lee, Y. Q. Zhang, and A. Leon-Garcia, "Information loss recovery for block-based image coding techniques—A fuzzy logic approach," IEEE Trans. Image Process., vol. 4, no. 3, pp. 259–273, Mar. 1995.

[5] H. Sun andW. Kwok, "Concealment of damaged block transform coded images using projections onto convex sets," IEEE Trans. Image Process., vol. 4, no. 4, pp. 470–477, Apr. 1995.

[6] Z. Wang, Y.L. Yu, and D. Zhang, "Best neighborhood matching: An information loss restoration technique for block-based image coding systems," IEEE Trans. Image Process., vol. 7, no. 7, pp. 1056–1061, Jul. 1998.

[7] W. Li, D. Zhang, Z. Liu, and X. Qiao, "Fast block-based image restoration employing the improved best neighbor-hood matching approach," IEEE Trans. Systems, Man, and Cybernetics, vol. 35, no. 4, pp. 546–555, Jul. 2005.

[8] D. Zhang and Z. Wang, "Image information restoration based on longrange correlation," IEEE Trans. Circuits Syst. Video Technol., vol. 12, no. 5, pp. 331–341, May 2002.

[9] C.S. Burrus, R. A. Gopinath, and H.Guo, Introduction to Wavelets and Wavelet Transform, Prentice-Hall, 1998.

[10] Shantanu D. Rane, J. Remus,and G. Sapiro, "Wavelet-domain reconstruction of lost blocks in wireless image transmission and packet-switched networks," International Conference on Image Processing 2002, vol. 1, pp. 309-312, 2002.

[11] Y.L. CHEN, C.T. HSIEH, and C.H. HSU, "Progressive Image Inpainting Based on Wavelet Transform", IEICE Trans. Fundamentals, Vol. E88-A, No.10, pp. 2826-2834, Oct.2005

[12] G.M. Davis, "A Wavelet-Based Analysis of Fractal Image Compression", IEEE Trans. Image Proc. Vol. 7, No. 2, pp. 141-154, 1997.

[13] Shantanu D. Rane, G. Sapiro, M. Bertalmio, "Structure and texture filling-in of missing image blocks in wireless transmission and compression applications," IEEE Trans. Image Processing, Vol. 12, Issue. 3, pp. 296 -303, March 2003.