CONCEALMENT OF DAMAGED BLOCK CODED IMAGES USING ADAPTIVE MULTILAYER PERCEPTRONS

Yu-Len Huang

Department of Applied Physics, Chung Cheng Institute of Technology
National Defense University, Ta-Hsi, Tao-Yuan, Taiwan, R.O.C.
Email: huangyl@ms2.hinet.net

ABSTRACT

Image coding algorithms such as vector quantization (VQ), JPEG, and MPEG utilize the block-based coding techniques to achieve the higher compression ratio. However, a cell loss or a random bit error during network transmission will permeate into the whole block and then generate several damaged blocks. Therefore, an efficient error concealment (EC) scheme is essential for diminishing the impact of damaged blocks in a compressed image. In this paper, a novel adaptive EC algorithm is proposed to conceal the error for block-based image coding systems by using neural network techniques in the spatial domain. In the proposed algorithm, only the intra-frame information is used for reconstructing the image with damaged blocks. Computer simulation results show that the visual quality and the PSNR evaluation of a reconstructed image are significantly improved by using the proposed EC algorithm.

1.INTRODUCTION

Block coded image and video compression techniques have been found to be efficient methods for low bit rate image coding. It has been adopted by most emerging image coding methods including JPEG [1], H.261 [2], H.263, MPEG-1 [3] and MPEG-2 [4]. In the past few years, JPEG and MPEG are widely used to encode images for reducing the transmission cost and storage capacity. Both the international standards use the block-based coding technique to achieve the higher compression ratio. However, as the images are highly compressed, the effect of cell loss or random bit error during network transmission becomes more serious. Thus, an efficient error concealment (EC) system is necessary for protecting image quality against transformation errors in the compressed image.

In 1993, Wang and Zhu proposed an EC method to recover the cell-loss for the DCT-based image coding [5]. In the paper, the DCT coefficients in a damaged block are estimated by utilizing the correlations between neighboring blocks. The optimal DCT coefficients can be estimated by imposing the smoothness constraints between the intensity values of adjacent samples. This EC algorithm is very efficient for DCT-coded images. Meanwhile, Narula and Lim compared various methods to diminish the impact of errors for digital HDTV applications [6] and Jung *et al*. proposed an EC algorithm in the spatial domain by using the projective interpolation [7]. Also, Sun and Kwok proposed a spatial interpolation algorithm for EC problem based on the projections onto convex set (POCS) theory [8]. We notice that the spatial projective interpolation schemes utilize different reconstruction rules that are decided by the edge pattern. If the block size is large or the edges in a block are irregular, the edge classification scheme will become complex and inefficient, and then the projective interpolation schemes will product poor performance for concealing the block errors. In 1997, a fast EC algorithm based on the DCT coefficient recovery technique and its applications to the MPEG video stream error is proposed by Park *et al*. [9]. Lately, Han and Leou proposed a detection and correction method for the transmission errors in JPEG compressed images [10]. However, the EC algorithms in [9-10] can be performed for only DCT-based coding systems. Thus, we attempt to develop an efficient and flexible algorithm to solve the cell loss problem for all block-based image-coding systems.

Artificial neural network techniques have been applied to solve complex problems in the fields of image processing and image compression. In the numerous neural networks, multilayer perceptron (MLP) network is particularly an efficiency model for the classification and prediction problems. Fundamentally, the MLP network is able to extract higher-order statistics by adding one or more hidden layers. The error back-propagation algorithm reported by Rumelhart [11] and Hirose [12] is that the most widely used for the construction of the MLP model. Hence, we employ this neural network model as the intensity predictor to estimate the pixels in damaged blocks. In the traditional EC algorithms, image reconstruction usually utilizes linear prediction functions to estimate the pixels in the damaged blocks. However, the linear prediction functions often produce wrong prediction for natural images. The proposed EC algorithm exploits the non-linearity property of the neural network models to reconstruct the damaged blocks more accurately.

The rest of this paper is organized as follows. Section 2 reviews the main features of MLP model and describes the construction of the MLP predictor with the back-propagation learning algorithm for the EC issue. Further, Section 3 presents the structure of the adaptive MLP error concealment algorithm in detail. Comparisons with other EC methods and the simulation results are given in Section 4. Finally, conclusions are drawn in Section 5.

2. MULTILAYER PERCEPTRONS

An MLP network contains several hidden layers. The function of the hidden layer neurons is to arbitrate between the input and the output of neural network. The input vector is fed into the source nodes in the input layer at first. The neurons of the input layer constitute the input signals applied to the neurons of the hidden layer. The output signals of the hidden layer are used as inputs to the next hidden layer. Finally, the output layer products the output results and then the neural computing process will be terminated. Among the algorithm used to design the MLP models, the back-propagation algorithm is the most popular one. In general, there are two different phases in the back-propagation algorithm, i.e., the forward phase and the backward phase. In the forward phase, the input signals are computed and passed through the neural network layer by layer. Then, the neurons in output layer product the output signals of the MLP. In this time, comparing the output response of the neural network with the desired response can generate the error signals. In the backward phase of the back-propagation algorithm, some free parameters used in the neural network can be adjusted by referring the error signals. This work can be used to minimize the distortion of the neural network.

We notice that the MLP model has the properties of high learning capability. Therefore, an MLP model with back-propagation learning algorithm is employed to correct the damaged block in the proposed EC algorithm. For this work, the on-line implementation of the back-propagation learning algorithm is iteratively executed from the training vectors and then products the synaptic weight vectors. An MLP network with the final synaptic weight vectors, it is used to reconstruct the compressed image with damaged blocks for the block-based coding systems.

3. ADAPTIVE MLP EC ALGORITHM

Before any EC techniques can be applied to the compressed images, the locations of damaged blocks are necessary first to be found out. In [13], Wang and Zhu review some of the effective error detection techniques for image and video coding systems. Obviously, these techniques can be employed straight in several block-based compression systems to detect the locations of damaged blocks effectively. In this paper, we only focus on the problem of concealing the error blocks for block-based image coding systems. We assume that the locations of damaged blocks are known and discuss techniques for concealing the detected errors.

Block-based image compression techniques first split an image into small size blocks and then encode these blocks. In order to reconstruct damaged block more accurately, most of the EC algorithms employ the edge-based classification, which utilizes the information of neighboring blocks surrounding the damaged block. In general, the edge direction or type is determined by exploiting the neighboring blocks for the damaged block. When the block size is small, the edge-based classification methods can obtain acceptable performance. However, if the block size is large, the edge property of a single block will become complex and complicated to classify the edge pattern. We propose a novel EC algorithm that contains a block size independent classification to determine the use of MLP predictor to reconstruct the damaged blocks. In the following, we first describe the basic structure of proposed EC algorithm that can conceal the separated damaged blocks in a decompressed image. Second, a complete EC algorithm is presented for concealing the image with irregular errors and consecutive damaged blocks.

3.1 Error Concealment for Images with Separated Lost Blocks

In the proposed EC algorithm, the average intensity values of four adjacent blocks (up, bottom, left, and right blocks) surrounding a damaged block are used as the inputs for block classification. We classify a single damaged block into five classes based on the adjacent blocks' gray-level intensity values. Let m_U, m_B, m_R, and m_L are the average intensity values of up block $\boldsymbol{U}$, bottom block $\boldsymbol{B}$, right block $\boldsymbol{R}$, and left block $\boldsymbol{L}$ for a damaged block $\boldsymbol{M}$, respectively. The mean values are used to determine the class of $\boldsymbol{M}$ by the classification rules described as follows

Class 0 (Smooth block): if $|m_U - m_B| < T$ and $|m_L - m_R| < T$.

Class 1 (Block intensity is increasing from right to left): if $|m_L - m_R| \geq T$ and $m_R > m_L$.

Class 2 (Block intensity is increasing from left to right): if $|m_L - m_R| \geq T$ and $m_R < m_L$.

Class 3 (Block intensity is increasing from up to bottom): if $|m_U - m_B| \geq T$ and $m_B > m_U$.

Class 4 (Block intensity is increasing from bottom to up): if $|m_U - m_B| \geq T$ and $m_U > m_B$.

where T is the predefined intensity distance threshold. Notices that when both $|m_U - m_B|$ and $|m_L - m_R|$ are larger than the T, the class of $\boldsymbol{M}$ is determined by the one with larger intensity distance. For example, if $|m_U - m_B|$ is larger than $|m_L - m_R|$, the block classifier will classify $\boldsymbol{M}$ into class 3 or class 4.

The proposed EC scheme uses five MLP predictors to correct the damaged blocks. In the beginning, the final synaptic weight vectors $\boldsymbol{w}$ for each class is produced by the back-propagation learning algorithm and used to construct the MLP network. Boundary pixels surrounding a damaged block are used for reconstructing the damage block as shown in Fig. 1. In order to conceal errors for the block with different sizes, the missing pixels within a damaged block are gradual estimated from outer to inner. By the spatial redundancy between the intensity values of adjacent samples, the MLP predictors utilize the boundary pixels surrounding the damaged block to estimate the outer pixels in the block. And then, the reconstructed pixels are used to estimate the inner pixels layer by layer. Finally, the MLP predictors can iteratively estimate all pixels in the damaged block. The adaptive MLP algorithm for a single damaged $n \times n$ block is described as follows,

Step 1. Determine the class of the damaged block.

Step 2. Set $i \leftarrow n$ and $k \leftarrow$ class number for the damaged block.

Step 3. Two boundary vectors of $(i+2)\times(i+2)$ and $(i+1)\times(i+1)$ blocks are combined and used as the input vectors of MLP network. The MLP predictor with the synaptic weight vectors $\boldsymbol{w}_{k,i}$ is used to estimate the boundary vector $\boldsymbol{x}_i$ for the $i \times i$ block.

Step 4. Store $\boldsymbol{x}_i$ into the damaged block at corresponding position and set $i \leftarrow i - 2$.

Step 5. If $i > 0$, then go to step 3.

The block diagram of the proposed EC scheme is shown in Fig. 2. For example, when an image is encoded with block size 8×8, the pixels surrounding a damaged block and the pixels in the block are shown in Fig. 3. The proposed EC algorithm first utilizes the surrounding pixels $a_{12,1..44}$ and $a_{10,1..36}$ as the input signals of MLP predictor. After the first neural network computing, the output can be stored into the outer boundary pixels $b_{8,1..28}$ for the damaged block. And then, the pixels $a_{10,1..36}$ and $b_{8,1..28}$ are used to estimate the pixels $b_{6,1..20}$. Using the same procedure, the estimated pixels for an 8×8 damaged block are combined from the output pixels of MLP predictors with the four different block sizes. Clearly, the proposed algorithm is always practical even if the edges in a compressed image are complex or irregular.

3.2. Error Concealment for Images with Neighboring Lost Blocks

Errors typically propagate through several consecutive blocks for compressed images and then yield some of adjacent lost blocks. In this condition, the proposed algorithm would fail to reconstruct the damaged blocks because there are no enough input signals for the MLP prediction. We design a pre-processing procedure for the proposed EC algorithm to conceal the neighboring damaged blocks in the decompressed images. In the proposed EC algorithm, the damaged blocks are reconstructed from top to bottom and left to right. As shown in Fig. 4(a), when a damaged block is reconstructing, each of the four neighboring blocks ***UL***, ***U***, ***UR***, and ***L*** must be a good block (no pixel is missing) or a reconstructed block. These blocks are called the processed blocks in this paper. The information in the processed blocks can be utilized for the MLP predictors as inputs directly in the proposed EC algorithm. On the contrary, the blocks ***R***, ***BL***, ***B***, and ***BR*** are the blocks that might also be the damage blocks. Thus, we call the blocks as the uncertain blocks. The pre-processing procedure is used to estimate the missing pixels in these uncertain blocks that are necessary inputs for concealing the currently reconstructed block. In this work, we also employ the MLP networks to reconstruct the necessary pixels. For blocks ***BL*** and ***BR***, only the four pixels in the corner near the currently reconstructed block are used as the inputs for the proposed EC algorithm. As shown in Fig. 4(b), the pixels b_1, b_2, b_3, and b_4 are estimated using the adjacent pixels a_1, a_2, a_3, a_4, c_1, c_2, c_3, and c_4 in the contiguous blocks. But in the situation that the pixels c_1, c_2, c_3, and c_4 are also missing, the estimation would be made only utilizing the pixels in the processed block. Similarly, the pixels needed for the proposed EC algorithm in blocks ***B*** and ***R*** can be estimated by using the same pre-processing procedure as shown in Fig. 4(c). Note that the worst case for a damaged block is that all of the uncertain blocks are also damaged. In this situation, at first, the necessary pixels in uncertain blocks ***R*** and ***BL*** will be estimated because of at least one processed block for ***R*** and ***BL*** can be found. Then the estimated pixels in ***R*** and ***BL*** are used to recover the necessary pixels in ***BR*** and ***B***, respectively. For illustration, Fig. 5(a) is an image with neighboring damaged blocks. The processed image that produced by the proposed pre-processing procedure is shown in Fig. 5(b). Moreover, the mean values of the estimated pixels in ***B*** and ***R*** are used as the $m_{\boldsymbol{B}}$ and $m_{\boldsymbol{R}}$ for the block classification in the proposed EC algorithm, respectively. Clearly, after the pre-processing procedure, the proposed EC algorithm can estimate all the damaged blocks in the error image.

Block diagram of the proposed EC algorithm with the pre-processing is summarized in Fig. 6. The whole proposed algorithm utilizes only one manner of neural network model - the MLP network. Thus, the architecture of the proposed EC algorithm with the pre-processing procedure is simple, redressing easily, and suitable for hardware design. Moreover, the MLP neural networks are highly parallel computer architecture and, thus, offer the potential for real-time applications.

4.SIMULATIONS

In the computer simulations, three-layer MLP networks are used as nonlinear predictors to reconstruct the damaged blocks for the images with block size 8×8. The pre-processing scheme employs two-layer MLP networks to estimate the necessary pixels surrounding the damaged blocks. The synaptic weights of the neural networks are generated by using the back-propagation learning algorithm. The training set includes five different monochrome images of size 512×512 with 256 gray levels (Boat, F-16, Sailboat, Tiffany, and Toys). Peak signal-to-noise ratio (PSNR) between the two images has been calculated to evaluate the performance of EC algorithm numerically. In this paper, we select the intensity threshold T as 10 for determining the class of a damaged block. In fact, the quality of the reconstructed images is similar for selecting T in the range 10 to 30 in the simulations.

In order to prove the precision of the proposed MLP prediction, we first compare the results using the proposed EC algorithm and simulation results of Jung's algorithm proposed in [7]. Table 1 shows the PSNR performances for the original image Lena with damaged blocks. This shows the proposed EC algorithm can obtain the better prediction. To show the differences of the reconstructed image using the proposed EC algorithm with and without the block classification, the enlarged portion in the reconstructed images Lena are given in Fig. 7(a) and Fig. 7(b), respectively. We observe that the proposed EC algorithm with block classification can really diminish the occurrence of blocking effects in reconstructed images.

Second, we compare the proposed EC algorithm with other algorithms performed for DCT-based image coding. The test image Lena is compressed with block size 8×8 by standard JPEG system. The bit rate of the compressed image is 0.60 bits per pixel (bpp) and the PSNR value is 35.9 dB. The locations of the damaged blocks are selected randomly. In the simulations, the block loss rate (BLR) is defined as the rate of the number of damaged block to the total number of blocks in the decompressed image. Also, the intensity values of the damaged blocks are initially replace by 128. As the simulation results in [9], it shows that Wang's algorithm [5] obtains the best PSNR performance in the EC algorithms. Hence, in this paper, a comparison is made only between the proposed algorithm and Wang's algorithm. The results of these two EC algorithms are presented in Fig. 8 and Table 2. It can be observed that the performance of the proposed algorithm is better than that of the Wang's algorithm. The average improvement for the 30 error images that with the BLR from 1% to 30% is 0.5 dB. We present the JPEG image Lena with 10% and 20% BLRs in Fig. 9(a) and Fig. 9(c), respectively. The reconstructed images for Fig. 9(a) and Fig. 9(c) using the proposed algorithm are shown in Fig. 12(b) and Fig. 9(d), respectively. In Figs. 9, we observe that both the smooth and detailed regions in the reconstructed images can obtain the good visual quality using the proposed EC algorithm. From the simulation results, we find that the proposed algorithm has very good performance.

5.CONCLUSIONS

In this paper, we proposed a novel adaptive EC algorithm using neural network techniques for the block-based image coding systems. The proposed algorithm reconstructs an error image only using its intra-band information and utilizes an intensity block classification procedure to avoid the disadvantages of the edge-based EC schemes. We adopt the MLP networks to accurately reconstruct all damaged blocks. The back-propagation learning algorithm is used to construct the synaptic weights for the MLP predictors in the proposed EC scheme. Moreover, a pre-processing procedure is performed to solve the problem of adjacent block loss for the proposed EC algorithm. In fact, an MLP network can be implemented easily by using VLSI techniques. The hardware design for the proposed EC scheme is simple and efficient. By comparing with other algorithms, the proposed EC algorithm obtains the superior performance for EC.

6.REFERENCES

[1] G. K. Wallace, "The JPEG still picture compression standard," *Commun. of the ACM*, vol. 34, no. 4, pp.31-44, Apr. 1991.

[2] M. Liou, "Overview of the px64 kbits/s video coding standard," *Commun. of the ACM*, vol. 34, no. 4, pp.59-63, Apr. 1991.

[3] D. L. Gall, "MPEG: A video compression for multimedia applications," *Commun. of the ACM*, vol. 34, no. 4, pp.47-58, Apr. 1991.

[4] Motion Picture Expert Group (JTC1/SC29/WG11) and Experts Group on ATM Video Coding (ITU-T SG15), "Generic coding of moving pictures and associated audio MPEG-2," Draft International Standard 13818, ISO/IEC, Nov. 1994.

[5] Q. F. Zhu, Y. Wang, and L. Shaw, "Coding and cell-loss recovery in DCT-based packet video," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 3, pp. 248-258, June 1993.

[6] A. Narula and J. S. Lim, "Error concealment techniques for an all-digital high-definition television system" in *SPIE Visual Communications and Image Processing*, 1993, vol. 2094, pp. 304-315.

[7] K. H. Jung, J. H. Chang, and C. W. Lee, "Error concealment techniques using projection data for block-based image coding" in *SPIE Visual Communications and Image Processin*, 1994, vol. 2308, pp. 1466-1476.

[8] H. Sun. Park and W. Kwok, "Concealment of damaged block transform coded images using projections on convex sets," *IEEE Trans. Image Pressing*, vol. 4, pp. 470-477, Apr. 1995.

[9] J. J. Park, J. W. Kim, and S. U. Lee, "DCT coefficients recovery-based error concealment technique and its application to the MPEG-2 bit stream error," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 7, no. 6, pp. 845-854, Dec. 1997.

[10] Y. H. Han and J. J. Leou, "Detection and correction of transmission errors in JPEG images," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 8, no. 2, pp. 221-231, Apr. 1998.

[11] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning representation by back-propagation errors," in *Nature*, 1986, vol. 323, pp. 533-536.

[12] Y. Hirose, K. Yamashita, and S. Hijiva, "Back-propagation algorithm which varies the number of hidden units," in *Neural Networks*, 1991, vol. 4, pp. 61-66.

[13] Y. Wang and Q. F. Zhu, "Error control and concealment for video communication: A review," *Proceedings of The IEEE*, vol. 86, no. 5, pp. 974-997, May 1998.

TABLE 1

The PSNR values (dB) of the images with damaged blocks and reconstructed images outside the training set.

Type of block loss	No EC	Jung's algorithm	Proposed algorithm without classification	Proposed algorithm
Every 2×2 block lost	20.7	33.1	32.9	33.4
Every 2 stripe lost	17.9	29.1	29.0	29.5

TABLE 2

The PSNR values (dB) of the reconstructed image Lena with damaged blocks in several different BLR.

BLR	No concealment	Wang's	Proposed
1%	31.7	35.4	35.5
2%	30.2	35.1	35.1
3%	28.7	34.8	35.0
4%	27.3	34.4	34.6
5%	26.8	34.1	34.3
6%	26.4	33.8	34.2
7%	25.8	33.5	34.0
8%	25.4	33.2	33.9
9%	24.6	33.0	33.6
10%	24.2	32.8	33.1
11%	23.8	32.5	32.8
12%	23.8	32.3	32.7
13%	23.2	32.0	32.7
14%	22.8	31.8	32.6
15%	22.8	31.5	32.4
16%	22.1	31.3	32.3
17%	22.1	31.1	32.2
18%	21.7	30.9	31.8
19%	21.7	30.7	31.4
20%	21.4	30.5	31.4
21%	21.1	30.3	30.9
22%	21.1	30.1	30.8
23%	20.9	29.8	30.6
24%	20.8	29.6	30.2
25%	20.5	29.3	30.1
26%	20.4	29.1	29.9
27%	20.2	29.0	29.7
28%	20.1	28.9	29.6
29%	19.7	28.7	29.2
30%	19.6	28.5	28.9

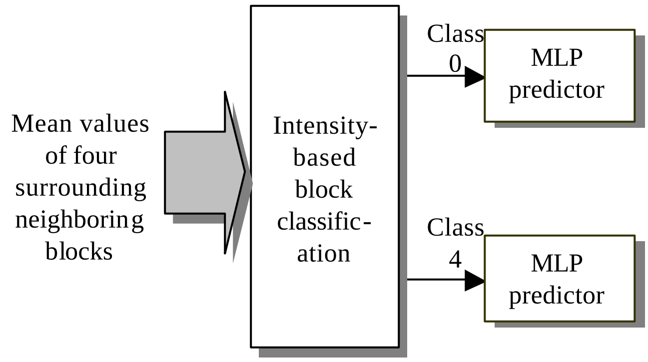


Fig. 1. The structure of damaged block classification approach.

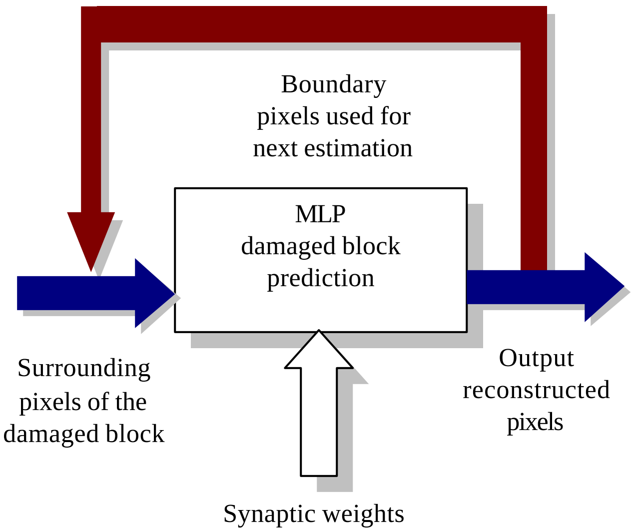


Fig. 2. Block diagram of the adaptive MLP error concealment scheme.

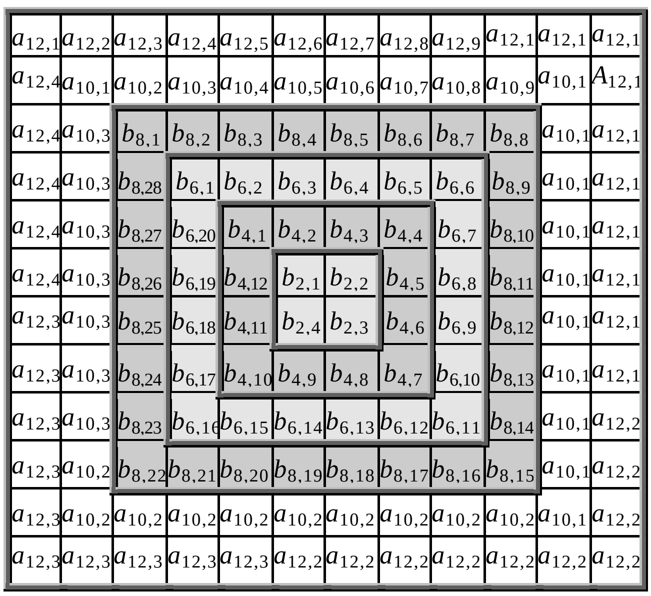
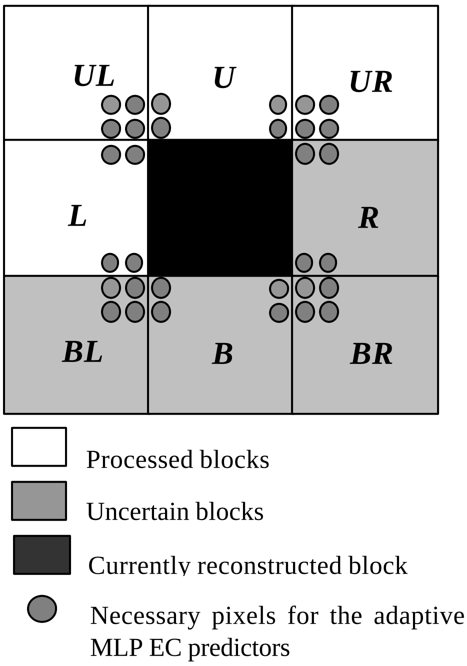
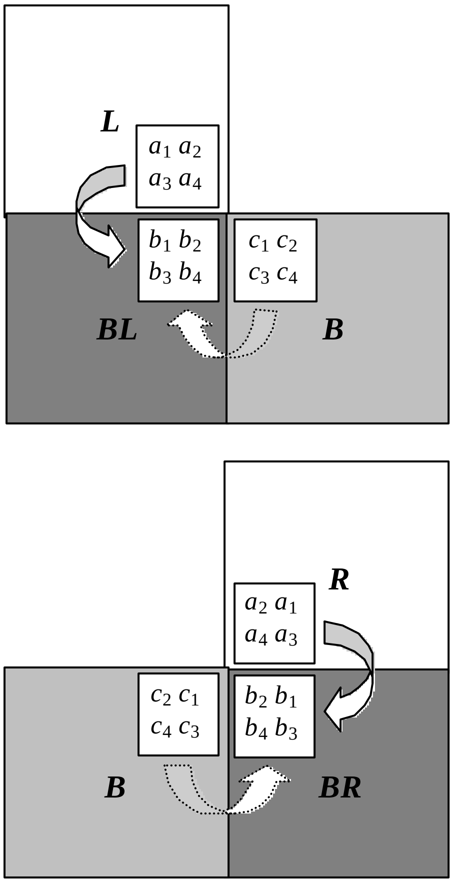


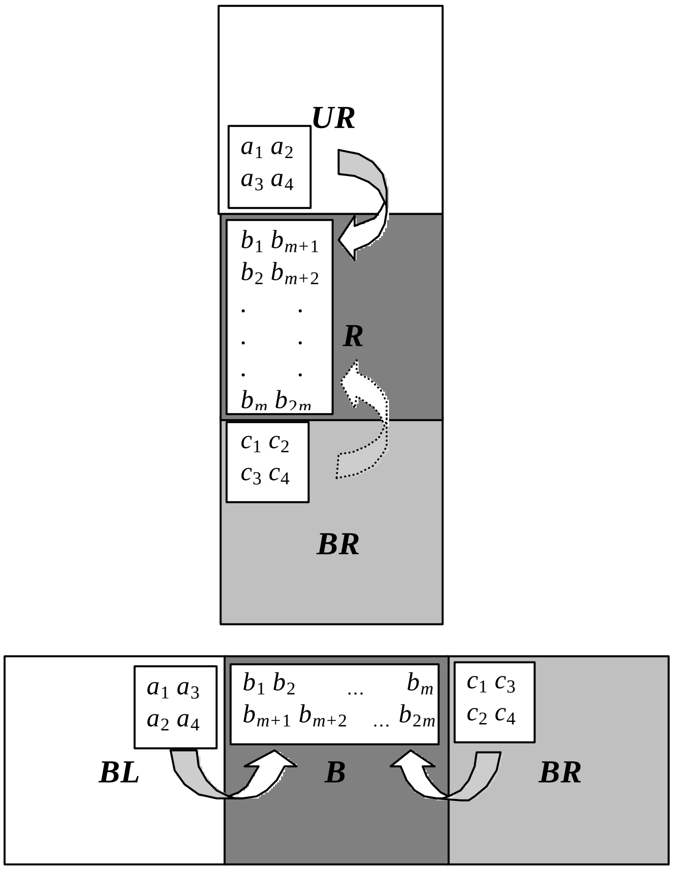
Fig. 3. Pixels surrounding and in a damaged 8×8 block.



(a)

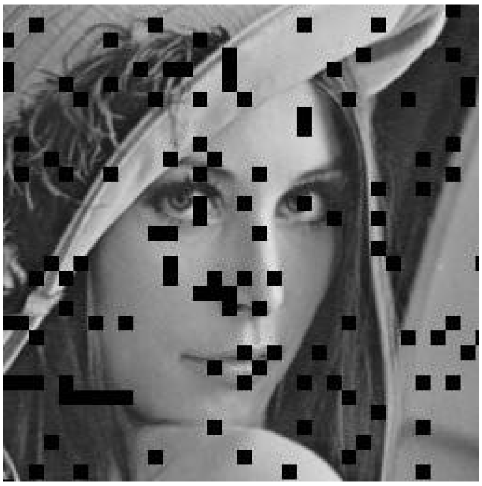


(b)

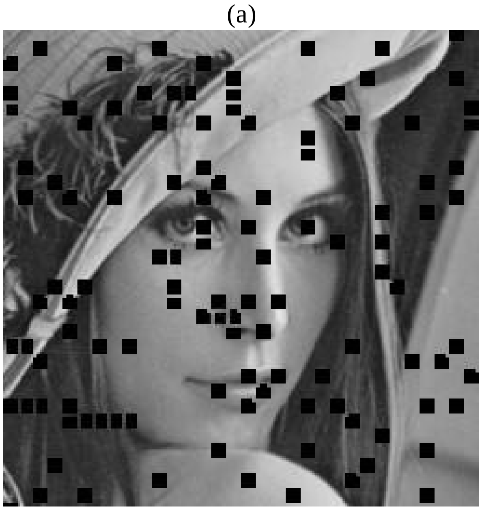


(c)

Fig. 4. (a) Necessary pixels for correcting a damaged block, (b) the adjacent blocks for the necessary pixel estimation of the blocks ***BL*** and ***BR***, and (c) the adjacent blocks for the necessary pixel estimation of the blocks ***R*** and ***B***.



(a)



(b)

Fig. 5. Illustration of the proposed pre-processing procedure: (a) an error image with neighboring damaged blocks, (b) the image after pre-processing.

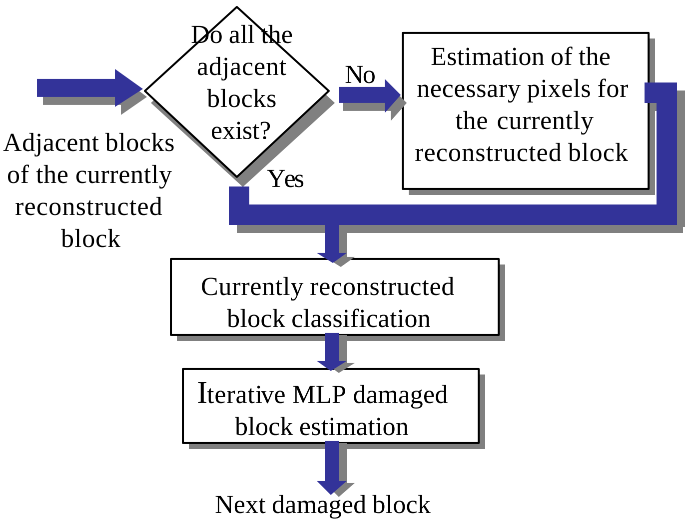


Fig. 6. Block diagram of the proposed adaptive EC algorithm with the pre-processing approach.

(a)

(b)

Fig. 7. Magnified portion of the reconstructed images using the proposed EC algorithm: (a) with block classification and (b) without block classification.

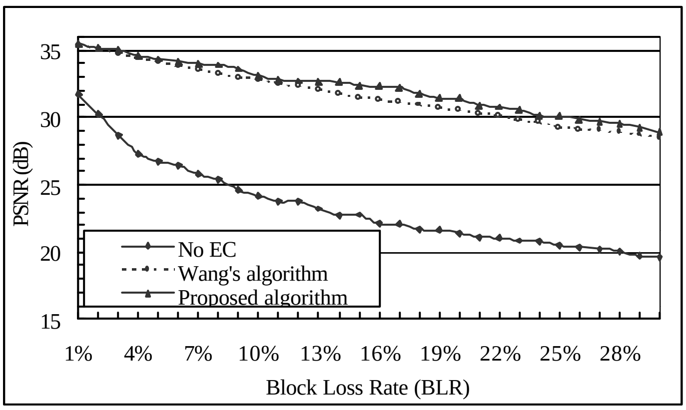


Fig. 8. PSNR performance of Wang's and proposed algorithms for Lena image.

(a)

(c)

(b)

(d)

Fig. 9. Results of the image Lena: (a) damaged image with 10% BLR, (b) reconstructed image using the proposed EC algorithm for (a), (c) damaged image with 20% BLR, and (d) concealed image by the proposed EC algorithm for (c).