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Error Concealment Using Adaptive Multilayer Perceptrons (MLPs) for Block-Based Image Coding*

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Image coding algorithms such as Vector Quantisation (VQ), JPEG and MPEG have been widely used for encoding image and video. These compression systems utilise block-based coding techniques to achieve a 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. The information of pixels surrounding a damaged block is used to recover the errors using the neural network models. Computer simulation results show that the visual quality and the PSNR evaluation of a reconstructed image are significantly improved using the proposed EC algorithm.

Keywords: Block-based image coding; Error concealment; Image restoration; Multilayer perceptron (MLP); Neural network; Transmission error

1. Introduction

Block-based image and video compression techniques such as Transform Coding (TC) and Vector Quantisation (VQ) have been found to be efficient methods for low bit rate image coding. In block-based image compression methods, the block-based Discrete Cosine Transform (DCT) is currently the most effective and popular technique for image and video representation and transmission. It has been adopted by most emerging image coding standards including JPEG [1], H.261 [2], H.263, MPEG-1 [3] and MPEG-2 [4]. In the past few years, JPEG and MPEG have been widely used to encode images for reducing transmission costs and storage capacity. Both the international standards use the block-based coding technique to achieve a 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.

So far, a number of papers have proposed concealing the cell loss or bit error. In 1993, Wang and Zhu proposed an EC method to recover the cell-loss for DCT-based image coding [5]. In that paper, the DCT coefficients in a damaged block are estimated by utilising the correlations between neighbouring 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].

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Also, Sun and Kwok proposed a spatial interpolation algorithm for the EC problem based on the projections onto convex set (POCS) theory [8]. We notice that the spatial projective interpolation schemes utilise 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 produce poor performance for concealing the block errors. Recently, a fast EC algorithm based on the DCT coefficient recovery technique and its applications to the MPEG video stream error was proposed by Park et al. [9]. Also Han and Leou proposed a detection and correction method for the transmission errors in JPEG compressed images [10]. However, those EC algorithms [9,10] can be performed only for DCT-based coding systems. Thus, we attempt to develop an efficient and flexible EC algorithm to solve the cell loss problem for all block-based image-coding systems, by using Spatial Predictive Concealment (SPC) techniques.

Artificial neural network techniques have been applied to solve complex problems in the fields of image processing [11–13] and image compression [14–16]. Among the numerous neural networks, the multilayer perceptron (MLP) network is a particularly efficient model for classification and prediction problems. Moreover, the MLP network is able to extract higher-order statistics by adding one or more hidden layers. The use of hidden neurons is particularly beneficial when the dimension of the input vector is large. In this paper, the proposed EC algorithm needs a large number of input vectors in neighbouring blocks surrounding a damaged block to recover the errors. The MLP network is able to learn complex tasks by extracting progressively more meaningful features from the input vectors, which is valuable for the SPC technique. Hence, we employed the MLP model as the intensity predictor to estimate the pixels in damaged blocks. In the traditional EC algorithms, image reconstruction usually utilises linear prediction functions to estimate the pixels in the damaged blocks. However, the linear prediction functions often produce wrong predictions for natural images. The proposed EC algorithm exploits the non-linearity property of the neural network models to reconstruct the damaged blocks more accurately. Consequently, the MLP model is a reliable choice for the proposed algorithm, because of the high capability of training and efficiency of computing.

The rest of this paper is organised as follows. Section 2 reviews the main features of the MLP model, and describes the construction of the MLP predictor with the backpropagation 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 Perceptron Models

An MLP model contains several hidden layers and the function of the hidden layer neurons is to arbitrate between the input and output of the neural network. The input vector is first fed into the source nodes in the input layer of the neural network. 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 produces the output results, and then the neural computing process is terminated. Among the algorithms used to design the MLP models, the error backpropagation algorithm reported by Rumelhart [17] and Hirose [18] is the most widely used and powerful algorithm for constructing the MLP model. In general, there are two different phases in the backpropagation algorithm, i.e. the forward and backward phases. In the forward phase, the input signals are computed and passed through the neural network layer by layer. Then, the neurons in the output layer produce 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 backpropagation algorithm, some free parameters used in the neural network can be adjusted by referring to the error signals. This work can be used to minimise any distortion of the neural network.

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

3. Adaptive MLP Error Concealment Algorithm

Before any EC techniques can be applied to the compressed images, the locations of damaged blocks first have to be found. Wang and Zhu [19] review some of the effective error detection techniques for image and video coding systems. Obviously, these techniques can be employed in several block-based compression systems to effectively detect the location of damaged blocks. Hence, in this paper, we focus only on the problem of concealing the error blocks for block-based image coding systems. For this work, we assume that the locations of the damaged blocks are known, and discuss techniques for concealing the detected errors.

Block-based image compression techniques first split an image into small sized blocks, and then encode these blocks. To reconstruct the damaged block more accurately, most of the EC algorithms employ edge-based classification, which utilises the information of neighbouring blocks surrounding the damaged block. In general, the edge direction or type is determined by exploiting the neighbouring blocks for the damaged block. Consequently, when the block size is small, the edge-based classification methods can obtain an 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. In fact, the block-based coding systems encode images or video with larger block sizes in order to achieve higher compression rates. Therefore, we propose a novel EC algorithm that contains a block-sised independent classification to determine the use of MLP predictors to reconstruct the damaged blocks. In the following, we first describe the basic structure of the proposed EC algorithm, which can conceal the separated damaged blocks in a decompressed image. Secondly, 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 of block classification. We classify a single damaged block into five classes, based on the adjacent blocks' grey-level intensity values. Let m_U, m_B, m_R and m_L be 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 $|m_L - m_R| < T$.

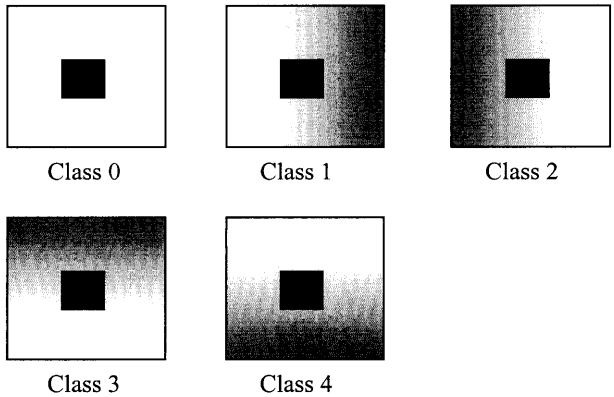


Fig. 1. Five classes in the proposed block intensity-based classification scheme. The black blocks denote the damaged block.

- **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 $m_U > m_B$.

Here T is the predefined intensity distance threshold. Figure 1 shows the five classes for a damaged block. Notice that when both $|m_U - m_B|$ and $|m_L - m_R|$ are larger than T, the class of $\boldsymbol{M}$ is determined by the one with a 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. Although this classification procedure is simple and rough, it is reliable for the proposed EC algorithm because of the high capability of the MLP network.

The proposed EC scheme uses five MLP predictors, and its corresponding MLP predictor corrects each of the damage blocks. In the beginning, the final synaptic weight vector $\boldsymbol{w}$ for each class is produced by the backpropagation learning algorithm, and is used to construct the MLP network. Boundary pixels surrounding a damaged block are used for reconstructing the damage block, as shown in Fig. 2. To conceal errors for the block with different sizes, the missing pixels within a damaged block are gradually estimated, from the outside in. By the spatial redundancy between the intensity values of adjacent samples, the MLP predictors utilise the

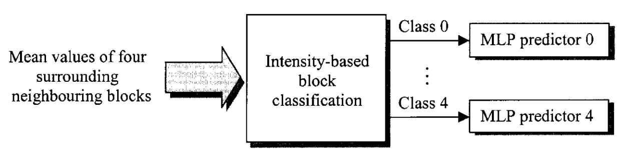


Fig. 2. The structure of damaged block classification approach.

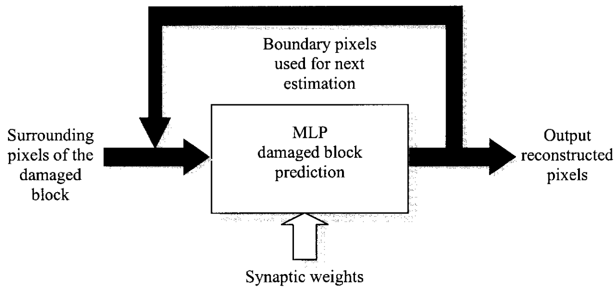


Fig. 3. Block diagram of the adaptive MLP error concealment scheme.

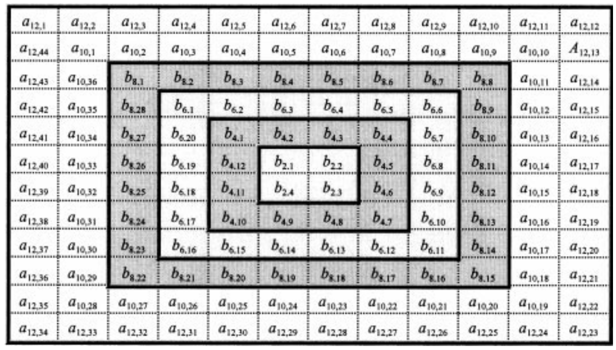


Fig. 4. Pixels surrounding and in a damaged 8 × 8 block.

boundary pixels surrounding the damaged block to estimated the outer pixels in the block. Then, the reconstructed pixels are used to estimate the inner pixels layer by layer. Finally, the MLP predictors can iteratively estimate all of the 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 for the damaged block using the classification rules.
- **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 the 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. 3. For example, when an image is encoded with a block size of 8 × 8, the pixels surrounding a damaged block and the pixels in the block are as shown in Fig. 4. The proposed EC

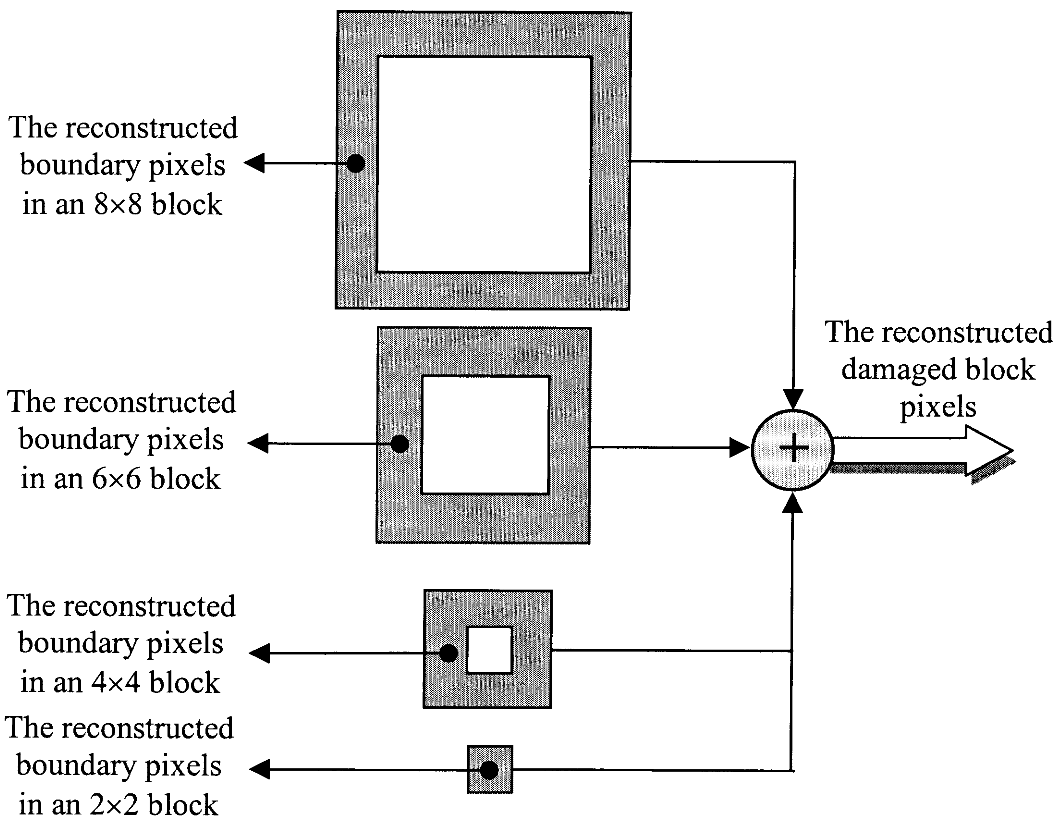


Fig. 5. The combination procedure of the reconstructed pixels for a damaged block.

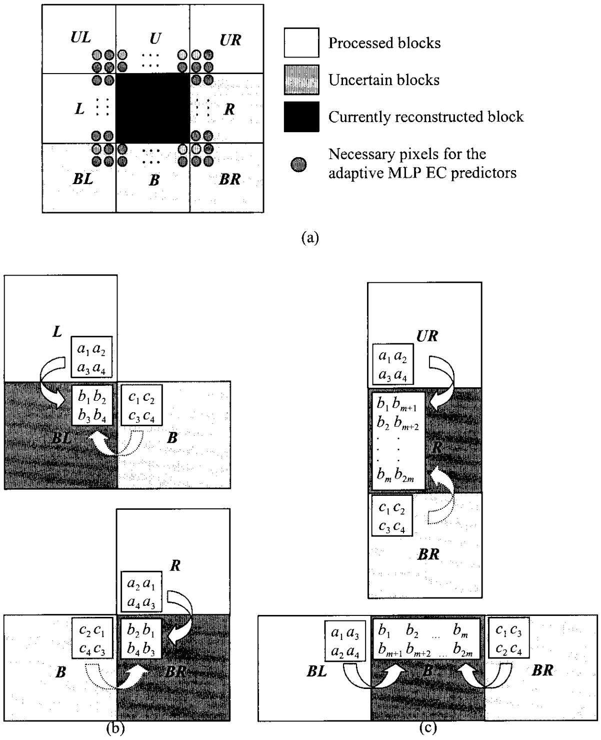


Fig. 6. (a) Necessary pixels for correcting a damaged block; (b) the adjacent blocks for the necessary pixel estimation of the blocks ***BL*** and ***BR***; and (c) the adjacent blocks for the necessary pixel estimation of the blocks ***R*** and ***B***.

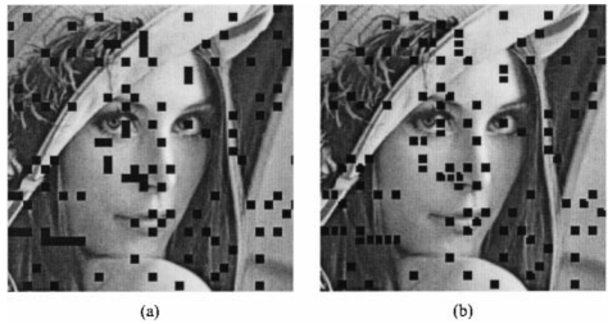


Fig. 7. Illustration of the proposed pre-processing procedure. (a) An error image with neighbouring damaged blocks; (b) the image after pre-processing.

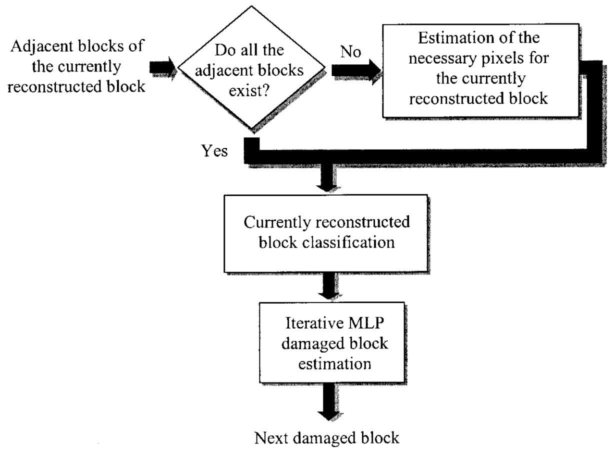


Fig. 8. Block diagram of the proposed adaptive EC algorithm with the pre-processing approach.

algorithm first utilises the surrounding pixels $a_{12,1\ldots44}$ and $a_{10,1\ldots36}$ as the input signals of the MLP predictor. After the first neural network is computed, the output can be stored into the outer boundary pixels $b_{8,1\ldots28}$ for the damaged block. Then, the pixels $a_{10,1\ldots36}$ and $b_{8,1\ldots28}$ are used to estimate the pixels $b_{6,1\ldots20}$. Using the same procedure, the estimated pixels for an 8×8 damaged block are combined from the output pixels of the MLP predictors with the four different block sizes. Figure 5 shows the combined procedure in the proposed EC algorithm. Clearly, the above algorithm is always practical even if the edges in a compressed image are complex or irregular.

3.2. Error Concealment for Images with Neighbouring Lost Blocks

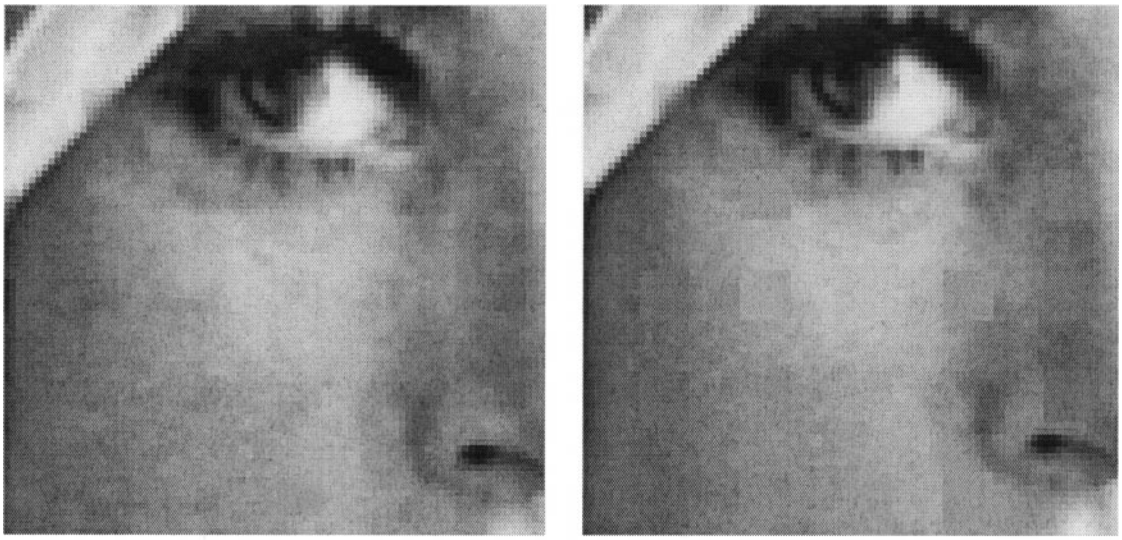
The proposed EC algorithm described previously assumes that the errors are localised to separated blocks in the decompressed image. In fact, errors typically propagate through several consecutive blocks for compressed images, and then yield some of the adjacent lost blocks. In this condition, the proposed algorithm would fail to reconstruct the damaged blocks because there are not enough input signals for MLP prediction. Hence, we have

Table 1. The PSNR values (dB) of 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

designed a pre-processing procedure for the proposed EC algorithm to conceal the neighbouring 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. 6(a), when a damaged block is reconstructing, each of the four neighbouring 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

Fig. 9. Results of the image Lena. (a) Error image with separated lost blocks; (b) reconstructed image using proposed algorithm for (a); (c) error image with striped lost blocks; and (d) reconstructed image for (c).



(a) (b)

Fig. 10. Results of the image Lena. (a) Magnified portion of the reconstructed image Fig. 9(b); (b) magnified portion of the reconstructed image using the proposed EC algorithm without block classification.

information in the processed blocks can be utilised for the MLP predictors as inputs directly in the proposed EC algorithm. On the contrary, blocks ***R, BL, B*** and ***BR*** are blocks that might also be the damaged blocks. Thus, we call the blocks 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. 6(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. However, in the situation that the pixels c_1, c_2, c_3 and c_4 are also missing, the estimation would be made only utilising the pixels in the processed block. Similarly, the pixels needed for the proposed

Table 2. The PSNR values (dB) of reconstructed image 'Lena' with damaged blocks in several different BLR.

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

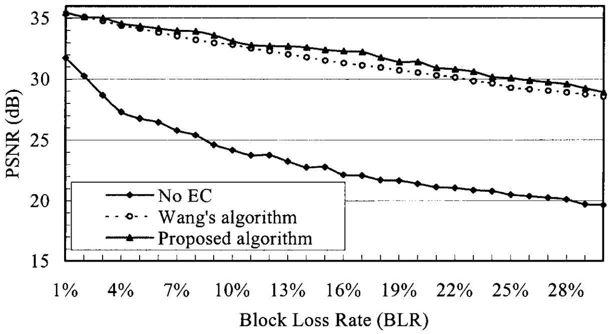


Fig. 11. PSNR performance of Wang's and the proposed algorithms for the Lena image.

EC algorithm in blocks ***B*** and ***R*** can be estimated by using the same pre-processing procedure as shown in Fig. 6(c). Note that the worst case for a damaged block is that all of the uncertain blocks are also damaged. In this situation, the necessary pixels in uncertain blocks ***R*** and ***BL*** will first be estimated because 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. 7(a) is an image with neighbouring damaged blocks. The processed image that is produced by the proposed pre-processing procedure is shown in Fig. 7(b). Moreover, the mean values of the estimated pixels in ***B*** and ***R*** are used as the m_B and m_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.

A block diagram of the proposed EC algorithm with pre-processing is summarised in Fig. 8. The proposed algorithm utilises only one neural network model, the MLP network. Thus, the architecture of the proposed EC algorithm with pre-processing is simple, redressing easily, and suitable for hardware design. Moreover, MLP neural networks are a highly parallel computer architecture, and thus offer the potential for real-time applications.

4. Simulations and Results

In the computer simulations, the three-layer MLP networks are used as nonlinear predictors to reconstruct the damaged blocks for the images with a block size of 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 the backpropagation learning algorithm from the training set of five different images (Boat, F-16, Sailboat, Tiffany and Toys). The images are monochrome images of size 512×512 with 256 grey levels. For the backpropagation learning algorithm, the initial synaptic weights are produced by a random number generation function at a floating interval [0–0.00001]. The learning rate parameter η = 0.01 is chosen to produce the final synaptic weight vectors because of the trade-off between the performance and computational speed. To evaluate the performance of the EC algorithm numerically, the Peak Signal-To-Noise Ratio (PSNR) between the two images has been calculated. In the proposed EC algorithm, 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 of 10 to 30 in the simulations.

To prove the precision of the proposed MLP prediction, we first compare the results using the proposed EC algorithm and the simulation results of Jung's algorithm [7]. Table 1 shows the PSNR performance for the original Lena image with damaged blocks. This shows that the proposed EC algorithm can obtain a better prediction. Figure 9(a) shows the image with every one out of four blocks damaged. Figure 9(c) is the image with every one out of two stripes lost. The damaged blocks in the image are replaced with level 128. The reconstructed images using the proposed algorithm for Figs 9(a) and 9(c) are shown in Figs 9(b) and 9(d), respectively. To show the differences among the reconstructed images using the proposed EC algorithm with and without the block classification, the enlarged portion in the reconstructed Lena images are given in Figs 10(a) and 10(b), respectively. We note that the proposed EC algorithm with block classification can really diminish the occurrence of blocking effects in reconstructed images.

Secondly, we compare the proposed EC algorithm with other algorithms performed for DCT-based image coding. The test Lena image is compressed with a block size of 8×8 by the 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 blocks to the total number of blocks in the decompressed image. Also, the intensity values of the damaged blocks are initially replaced by 128. The simulation results of two SPC algorithms, namely Wang's algorithm [5] and the proposed algorithm, are presented in Fig. 11 and Table 2. Wang's algorithm has been shown to be an efficient SPC algorithm for image and video

Fig. 12. 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).

communication [5,9,19–22]. It can be observed that the performance of the proposed algorithm is better than that of 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 Lena image with 10% and 20% BLRs in Figs 12(a) and 12(c), respectively. The reconstructed images for Figs 12(a) and 12(c) using the proposed algorithm are shown in Figs 12(b) and 12(d), respectively. In Fig. 12, we observe that both the smooth and detailed regions in the reconstructed images can obtain 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 have proposed a novel adaptive EC algorithm using neural network techniques for block-based image coding systems. The proposed algorithm reconstructs an error image only using its intra-band information, and utilises an intensity-based block classification procedure to avoid the disadvantages of the edge-based EC schemes. We adopt MLP networks to accurately reconstruct all of the damaged blocks. The backpropagation 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 using VLSI techniques. The hardware design for the proposed EC scheme is simple and efficient. By comparison with other algorithms, the proposed EC algorithm obtains a superior performance for error correction. From the experimental results, we find that the proposed algorithm is expected to be a useful EC algorithm for block-based image coding systems. In future work, we will extend the proposed algorithm to other image and video compression applications, such as videoconferencing, video on demand and high-definition TV.

References

1. Wallace GK. The JPEG still picture compression standard. Commun ACM 1991; 34(4): 31–44
2. Liou M. Overview of the px64 kbits/s video coding standard. Commun ACM 1991; 34(4): 59–63
3. Gall DL. MPEG: A video compression for multimedia applications. Commun ACM 1991; 34(4): 47–58
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. November 1994
5. Zhu QF, Wang Y, Shaw L. Coding and cell-loss recovery in DCT-based packet video. IEEE Trans Circuits Syst Video Technol 1993; 3: 248–258
6. Narula A, Lim JS. Error concealment techniques for an all-digital high-definition television system. SPIE Visual Commun and Image Process 1993; 2094: 304–315
7. Jung KH, Chang JH, Lee CW. Error concealment techniques using projection data for block-based image coding. SPIE Visual Commun and Image Process 1994; 2308: 1466–1476
8. Sun H, Kwok W. Concealment of damaged block transform coded images using projections on convex sets. IEEE Trans Image Process 1995; 4: 470–477
9. Park JJ, Kim JW, Lee SU. DCT coefficients recovery-based error concealment technique and its application to the MPEG-2 bit stream error. IEEE Trans Circuits Syst Video Technol 1997; 7(6): 845–854
10. Han YH, Leou JJ. Detection and correction of transmission errors in JPEG images. IEEE Trans Circuits Syst Video Technol 1998; 8(2): 221–231
11. Chen DR, Chang RF, Huang YL. Computer-aided diagnosis applied to US of solid breast nodules using neural networks. Radiology 1999; 213: 407–412
12. Cios KJ, Shin I. Image recognition neural network: IRNN. Neurocomputing 1995; 7: 159–185
13. Mingolla E, Ross W, Grossberg S. A neural network for enhancing boundaries and surfaces in synthetic aperture radar images. Neural Networks 1999; 12: 499–511
14. Karayiannis NG, Pai PI. Fuzzy algorithms for learning vector quantization. IEEE Trans Neural Networks 1996; 7(5): 1196–1211
15. Rizvi SA, Nasrabadi NM. Finite-state residual vector quantisation using a tree structured competitive neural network. IEEE Trans Circuits Systems Video Technol 1997; 7(2): 377–390
16. Jiang J. Image compression with neural networks-A survey. Signal Processing: Image Commun 1999; 14: 737–760
17. Rumelhart DE, Hinton GE, Williams RJ. Learning representation by backpropagation errors. Nature 1986: 323: 533–536
18. Hirose Y, Yamashita K, Hijiva S. Back-propagation algorithm which varies the number of hidden units. Neural Networks 1991; 4: 61–66
19. Wang Y, Zhu QF. Error control and concealment for video communication: A review. Proc IEEE 1998; 86(5): 974–997
20. Wang Y, Zhu QF, Shaw L. Maximally smooth image recovery in transform coding. IEEE Trans Commun 1993; 41: 1544–1551
21. Kwok W, Sun H. Multi-directional interpolation for spatial error concealment. IEEE Trans Consummer Electron 1993; 39: 455–460
22. Zhu QF, Wang Y. The use of second order derivative based smoothness measure for error concealment in transform based codecs. Proc SPIE Visual Commun and Image Process 1995; 1205–1214