Error Concealment using Neural Networks for Block-Based Image Coding

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Abstract: *In this paper, a novel adaptive error concealment (EC) algorithm, which lowers the requirements for channel coding, is proposed. It conceals errors in block-based image coding systems by using neural network. In this proposed algorithm, only the intra-frame information is used for reconstruction of the image with separated 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 MSE evaluation of a reconstructed image are significantly improved using the proposed EC algorithm. We propose also a simple non-neural approach for comparison.*

Keywords

Block-based image coding, error concealment, image restoration; multilayer perceptron, radial basis function network, mobile radio channels.

1. Concealment of Error Blocks

JPEG and MPEG algorithms have been widely used for image encoding to reduce transmission costs and storage capacity. Both the international standards use the block-based coding techniques 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 to protect the image quality against transmission errors in the compressed image.

The most frequently used EC methods for transmission e. g. over radio channels are Forward Error Correction (FEC) at physical layer and Automatic Retransmission Request (ARQ) [14] at the transport layer. In order to improve a channel condition of wireless links, powerful channel codes are often used at the expense of bandwidth.

We propose a novel robust system that lowers the requirements for channel coding (bandwidth requirements).

2. Neural Network Models

Artificial neural network (NN) techniques have been applied to solve complex problems in the fields of image processing [1–3] and image compression [4–6, 13]. Multilayer perceptron (MLP) and radial basis functions (RBF) network are particularly efficient models for classification and prediction problems. We employed the MLP and RBF network models as the intensity predictor to estimate the pixels in damaged blocks. The proposed EC algorithm exploits the non-linearity property of the neural network models to reconstruct the damaged blocks more accurately.

Fig. 1. Image Train used for training of MLP and RBF networks.

2.1 Multilayer Perceptron

Basic multilayer perceptron (MLP) building unit is a model of artificial neuron. This unit computes the weighted sum of the inputs plus the threshold weight and passes this sum through the activation function (usually sigmoid) [10]:

$$v_j = \theta_j + \sum_{i=1}^{p} w_{ji} x_i = \sum_{i=0}^{p} w_{ji} x_i \tag{1}$$

$$y_j = \varphi_j (v_j) \tag{2}$$

where v_j is a linear combination of inputs x_1, x_2, …, x_p of neuron j, $w_{j0}=\theta_j$ is the threshold weight connected to the special input x_0=-1, y_j, is the output of neuron j and $\varphi_j(\ )$ is its activation function. Herein we use the special form of sigmoidal (non-constant, bounded, and monotone-increasing) activation function - logistic function

$$y_j = \frac{1}{1+\exp(-v_j)}. \tag{3}$$

In a multilayer perceptron, the outputs of the units in one layer form the inputs to the next layer. The weights of the network are usually computed by training the network using the backpropagation (BP) algorithm reported by Rumelhart [7] and Hirose [8].

A multilayer perceptron represents nested sigmoidal scheme [10], its form for single output neuron is

$$F(\mathbf{x},\mathbf{w}) = \varphi\left(\sum_j w_{oj}\varphi\left(\sum_k w_{jk}\varphi\left(\ldots\varphi\left(\sum_i w_{li}x_i\right)\ldots\right)\right)\right) \tag{4}$$

where $\varphi(\ )$ is a sigmoidal activation function, w_{oj} is the synaptic weight from neuron j in the last hidden layer to the single output neuron o, and so on for the other synaptic weights, x_i is the i-th element of the input vector $\mathbf{x}$. The weight vector $\mathbf{w}$ denotes the entire set of synaptic weights ordered by layer, then neurons in a layer, and then number in a neuron.

We remark, 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 on line implementation of the backpropagation learning algorithm is iteratively executed from the training vectors, and it produces the synaptic weight vectors consequently. An MLP network with the final synaptic weight vectors is used to reconstruct the damaged blocks of an image in the proposed schemes.

2.2 Radial Basis Function Network

RBF network [10], [11] is based on a multivariable interpolation: Given a set of $\boldsymbol{N}$ distinct vectors $\{\mathbf{x}_i \in R^p | i=1,\ldots,N\}$ and N real numbers $\{d_i \in R | i=1,\ldots,N\}$, the aim is to find a function $f: R^p \to R$ satisfying the condition $f(\mathbf{x}_i)=d_i, \forall i=1, \ ,N.$

RBF approach works with N radial basis functions (RBF) ϕ_i, where ϕ_i: $R^p \to R$, $i=1, \ ,N$ and $\phi_i = \phi(\|\mathbf{x}-\mathbf{c}_i\|)$, where $\phi: R^+ \to R$, $\mathbf{x} \in R^p$, $\|\ \|$ is a norm on R^p, $\mathbf{c}_i \in R^p$ are centers of RBFs. Centers are set to $\mathbf{c}_i=\mathbf{x}_i \in R^p$, $i=1,\ldots,N$. Very often used form of RBF is the Gaussian function $\phi(x)=\exp(-x^2/2\sigma^2)$, where σ is a width (parameter). Functions ϕ_I $i=1,\ldots,N$ form the basis of a liner space and interpolation function f is their linear combination

$$f(\mathbf{x}) = \sum_{j=1}^{N} w_j \phi(\|\mathbf{x}-\mathbf{c}_j\|). \tag{5}$$

Interpolation problem is simple to solve, in contrast to approximation problem (there is N given points and n_0 functions ϕ, where $n_0<N$.), which is more complicated. Then it is a problem to set centers $\mathbf{c}_i$ $i=1,\ldots,n_0$, also parameter σ of each RBF can be not the same for all RBFs. One possible solution for RBF approximation problem is a neural network solution. RBF network is a feed forward network consisting of input, one hidden and output layer. Input layer distributes input vectors into the network, hidden layer represents RBFs ϕ. Linear output neurons compute linear combinations of their inputs. RBF network learning consists of more different steps (description of RBF network learning can be found in [10], [11]).

The RBF model is suitable for data interpolation and classification. For this work, the RBF model was trained from the selected input vectors producing the synaptic weight vectors. An RBF network with the final synaptic weight vectors is used to reconstruct the damaged blocks for the block-based coding systems.

The MLP and RBF predictors have been trained from an image called Train of size 512x512 pixels shown in Fig.1.

3. Adaptive EC Algorithm

Before any EC technique can be applied to the damaged images, the locations of erroneous blocks have to be found. Wang and Zhu [9] 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 detect the location of damaged blocks effectively. In this paper, we focus not on the detection, but on the problem of concealing the error blocks in block-based image coding systems. We assume that the locations of the damaged blocks are known, and discuss techniques for concealing the detected errors.

3.1 EC of Separated Blocks (BNN Method)

The proposed EC scheme uses one MLP or RBF predictor which corrects each of the damaged blocks. Boundary pixels surrounding a block are used for its reconstruction, as shown in Fig. 2. Pixels *b1, ..., b80* represent the input vector of the neural network. Pixels *a1, ..., a64* are representing the 8x8 block being repaired – the output vector of the neural network. Both neural network models were trained using samples extracted from the TRAIN image (Fig. 1) and tested with other selected images.

3.2 EC with Block Classification (BNNC Method)

In this EC algorithm, the average intensity values of four adjacent blocks (upper (U), bottom (B), left (L) and right (R) blocks) surrounding a corrupted block are used as the inputs for block classification. We classify a single damaged blocks into the five classes, depending on the adjacent blocks' grey-level intensity values [12]. 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. We propose two methods for blocks classification:

a) ***CA Method*** - Let m_U, m_B, m_R and m_L are the average intensity values of upper block U, bottom block B, right block R and left block L they surround a damaged block M.

b) ***CL Method*** - Let m_U, m_B, m_R and m_L are the average intensities of 2x12 pixels shown in Fig. 2 (two rows *b1-b24* for m_U, two rows *b57-b80* for m_B, two columns *b11-b80* for m_R and two columns *b1-b70* for m_L).

The mean values are used to determine the class of M using the following classification rules:

- **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 up): if $|m_U - m_B| \geq T$ and $m_B < m_U$.

The value of threshold T depends on a processed image. The proposed EC scheme uses five MLP or RBFN predictors, and its corresponding MLP/RBFN predictor corrects each of the damaged blocks. Boundary pixels surrounding a damaged block are used for reconstructing the block, as shown in Fig. 2.

3.3 Side Method (SM)

This non-neural EC method is used for comparison with neural methods. It is based on the assumption that the intensity of the block is changing from left to right or up to bottom. We can compute the way how the intensity differs from the block's neighborhood.

According to Fig. 2, each of the *a1-a64* pixels is determined as follows: we use two corresponding b-pixels on the left side and two on the right side of the corresponding row and calculate the difference of their intensity means. This value divided by 9 (number of pixels in a row + 1) sets the incremental intensity step by which the damaged a-pixels in the row are obtained one by one in this 'left to right SM procedure'.

b1	b2	b3	b4	b5	b6	b7	b8	b9	b10	b11	b12
b13	b14	b15	b16	b17	b18	b19	b20	b21	b22	b23	b24
b25	b26	a1	a2	a3	a4	a5	a6	a7	a8	b27	b28
b29	b30	a9	a10	a11	a12	a13	a14	a15	a16	b31	b32
b33	b34	a17	a18	a19	a20	a21	a22	a23	a24	b35	b36
b37	b38	a25	a26	a27	a28	a29	a30	a31	a32	b39	b40
b41	b42	a33	a34	a35	a36	a37	a38	a39	a40	b43	b44
b45	b46	a41	a42	a43	a44	a45	a46	a47	a48	b47	b48
b49	b50	a49	a50	a51	a52	a53	a54	a55	a56	b51	b52
b53	b54	a57	a58	a59	a60	a61	a62	a63	a64	b55	b56
b57	b58	b59	b60	b61	b62	b63	b64	b65	b66	b67	b68
b69	b70	b71	b72	b73	b74	b75	b76	b77	b78	b79	b80

Fig. 2. The reconstructed block and its neighborhood.

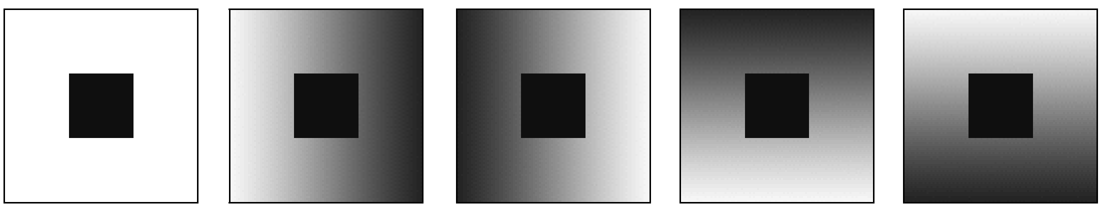
The next procedure differs from the left-to-right only by using two corresponding b-pixels on the up side and two on the bottom side of the damaged block. Final a-pixel intensity is the mean value of these two SM procedures results. Here T is the predefined intensity distance threshold. Fig. 3 shows the five classes of a damaged block. We want to note, 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.

4. 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 using only its intra-frame information and utilizes an intensity based block classification procedure to avoid the disadvantages of the edge-based EC schemes. We used MLP and RBF networks to reconstruct all of the damaged blocks accurately. Moreover, a preprocessing procedure is performed to solve the problem of adjacent block loss for the proposed EC algorithm.

As an objective quality criterion, we used MSE measure. In Fig. 4, the comparison chart of MSE for the image Nella can be seen. This chart corresponds to Fig. 5. We compare the results of different approaches for two cases:

1. all blocks (ALL) of the image were processed
2. only corrupted blocks (BAD) were processed.



CLASS 0 CLASS 1 CLASS 2 CLASS 3 CLASS 4

Fig. 3. Five classes in the proposed classification scheme -- the black block denotes the damaged block.

In Fig. 5, the images after reconstruction using different neural networks are presented.

For illustration of the performance of the described methods, we applied the concealment procedure to the whole image, i.e. to all blocks of the selected images. We use the image called Nella, which is the region of image Lena of the size 256x256 pixels (Fig.5.a.). Fig.5.b) presents the result of error concealment method without block classification using the MLP network with 80 input neurons, 144 hidden neurons and 64 output neurons (BNN_MLP_80_144_64).

In Fig.5.c) we can see the result of error concealment method without block classification using the RBF network with 80 input neurons, 100 hidden (RBF) neurons and 64 output neurons (BNN_rbf_80_100_64). Fig.5.d) differs from the previous one in the number of hidden neurons (BNN_rbf_80_150_64). The next two images - Fig. 5e, (BNNC_MLP_80_144_64_CA), and Fig. 5f) (BNNC_MLP_80_144_64_CL) correspond to error concealment with block classification (BNNC–CA and CL methods) using the MLP network with 80 input neurons, 144 hidden neurons and 64 output neurons. Fig.5.g (BNNC_rbf80_100_64_CA) and Fig. 5.h (BNNC_rbf_80_144_64_CA) show the results of the same method - error concealment with block classification (BNNC–CA method) using the RBF network with 80 input neurons and 64 output neurons. They differ from each other in the number of hidden neurons (100 and 144 hidden neurons). Fig.5.i) illustrates the result of non–neural Side Method.

In Fig.6, the comparison of results for images Nella, Baboon, House and Einstein, repaired using BNN method with MLP 80-144-64 neural network is shown. From Fig. 4 and 5, it results that MLP 80-144-64 gives the best concealment results (MSE = 215, 78).

Fig. 6 shows the comparison chart of the reconstruction of all blocks (ALL) and bad blocks only (BAD) of the images repaired using BNN method with MLP 80-144-64 neural network. This chart corresponds to Fig. 7.

In fact, MLP and RBF networks can be implemented easily using VLSI technology. The hardware design for the proposed EC scheme is simple and efficient. The proposed neural network EC algorithms yield good performance for error correction. Taking the experimental results into account, we expect that proposed algorithms will be a successful part of block-based image coding systems.

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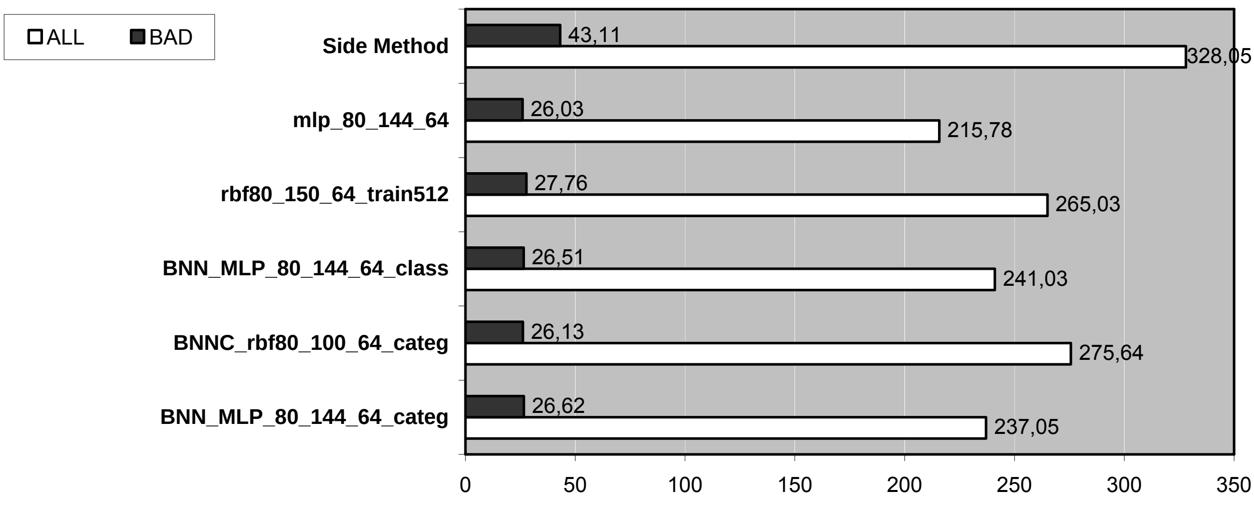

Fig. 4. The comparison chart of MSE for the reconstruction of all blocks (ALL) and only bad blocks (BAD) of the image Nella using different networks.

a) Original nella

b) BNN_MLP_80_144_64, MSE=215.78

c) BNN_rbf_80_100_64 MSE=267.39

d) BNN_rbf_80_150_64, MSE=265.03

e) BNNC_MLP_80_144_64_CA, MSE=237.05

f) BNNC_MLP_80_144_64_CL, MSE=241.03

g) BNNC_rbf80_100_64_CA, MSE=275.64

h) BNNC_rbf80_144_64_CA, MSE=297.25

i) Side Method, MSE=328.05

Fig. 5. The comparison of the reconstruction of all blocks of the image NELLA using different networks.

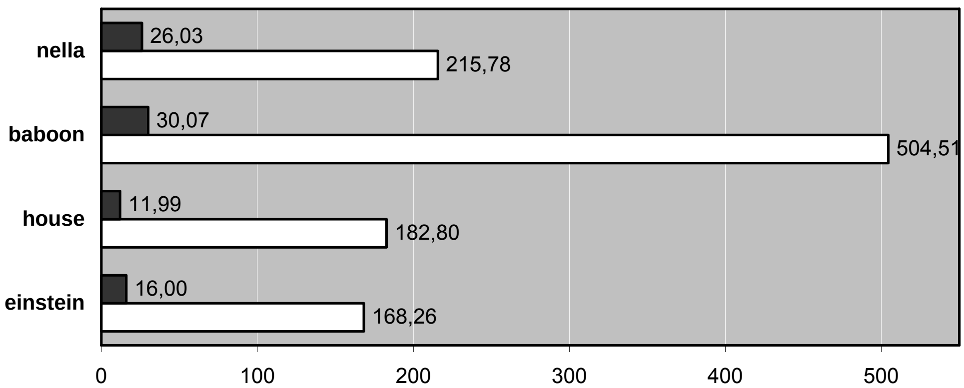

Fig. 6. The comparison chart of MSE for the reconstruction of all blocks (ALL) and only bad blocks (BAD) of the images repaired using BNN method with MLP 80-144-64 neural network.

a) Image nella containing bad blocks

b) nella – repaired BAD only, MSE=26.03

c) nella – repaired ALL blocks, MSE=215.78

d) Image baboon containing bad blocks

e) baboon – repaired BAD only, MSE=30.07

f) baboon – repaired ALL, MSE=504.51

g) Image house containing bad blocks

h) house – repaired BAD only, MSE=11.99

i) house– repaired ALL, MSE=182.80

j) Image einstein containing bad blocks

k) einstein – repaired BAD only, MSE=16.00)

l) einstein– repaired ALL, MSE=168.26

Fig. 7. The comparison of images Nella, Baboon, House and Einstein repaired using BNN method with MLP 80-144-64 neural network

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