SEQUENTIAL BEST RANGE MATCHING: AN ERROR CONCEALMENT TECHNIQUE WITH APPLICATION IN HIGH PACKET LOSS IMAGE TRANSMISSION

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ABSTRACT

Suffering from the inadequacy of reliable received data and their lack of sufficient *a priori* knowledge about the lost regions, the existing error concealment (EC) techniques fail to perform well in high packet loss transmission of compressed images. In order to obviate such a deficiency, we propose the *sequential best range matching* (SBRM) algorithm: the correctly received regions of image are employed to fabricate the lost regions according to the spatial similarities within the image. Our simulation results show that SBRM not only outperforms the existing EC methods especially in high packet loss conditions, but also provides suitable prior knowledge to initialize further estimation and denoising processes.

Index Terms— Still Image Transmission, Sequential Recovery, Error Concealment

1. INTRODUCTION

A variety of image and video coding systems has been developed for efficient signal transmission over capacity limited channels. Popular visual compression standards such as JPEG and MPEG treat the image(s) as a collection of non-overlapping blocks. One of the critical advantages of such block-wise standards is their modal compatibility with packet-switched transmission protocols which are widely network communication utilized in architectures. Nevertheless, any channel impairment may incur severe visual inefficiency because of the packet based substance of transmission. That is even a single bit error may cause a packet loss that causes loss of a block of the transmitted image. In high error rates and/or high traffic networks, forward error correction (FEC) and automatic repeat request (ARQ) schemes cannot help.

The family of error concealment (EC) techniques generally aims to employ the inherent redundancy in natural images to reconstruct the lost parts. The performance of an EC technique depends on the accuracy of model used to characterize the spatial correlations within the image. While no general model accurately describes images, one can say that an image may contain complex textures, dominant edges, stripes, and smooth regions. An ideal EC technique should be able to contend with all types of loss.

Numerous EC methods assume deterministic models to describe the blockwise dependency within the images, which is employed by the reconstruction process in either spatial or spectral domain. Those methods generally employ estimation approaches to recover the representing coefficients of lost regions subject to limited order criterions such as MSE, and since they are essentially lowpass (smoothing) filters, they fail to reconstruct the edges or complex textures [3]. The main inadequacy of those approaches refers to the lack of a priori knowledge about the substance of the lost region, and also, the weakness of local Gaussian stationary assumption [4]. Some methods impose simplified edge models [5] or shape preserving approaches [6] to reveal boundaries within the image so that the smoothing procedure improves subject to the knowledge about the segmentations of image. It should be noted that those approaches also suffer from the incapability of coping with mixed textures such as stripes, where the missing region contains a number of edges none of which is dominant.

Recently, some methods [7]-[9] employ data hiding techniques in order to embed important features of the image within it. This way, in the case of missing a region, we still have some information about the lost part that can be utilized to sufficiently initialize and guide the recovery procedure (e.g., select the mode of reconstruction in hybrid EC methods). Selection of suitable features for recovery is of great importance as the subsequent compression usually does not leave much room for robust embedding of data. Unfortunately, most of prior studies utilize an over simplified formulation of EC problem that considers only the effect of channel impairment and neglect the effect of source quantization [2]. Thus, practical use of such data hiding based EC methods is questionable.

The Best Neighborhood Matching (BNM) method prepares primary knowledge about the missing regions by comparing its neighborhood with the other intact regions within the image and selects the best matching candidate to recover the missing part [1]. Since BNM is a *parallel*

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recovery method (i.e., it simultaneously recovers all the pixels inside the missing region), the availability of intact regions in the searching area is critical. That is why BNM performs well in low error rate situations (up to 15% packet losses).

In this paper, the Sequential Best Range Matching (SBRM) is proposed as a promising modification of BNM; the corrupted regions are recovered in a sequential manner so that the recovery relies on both previously recovered and the intact received regions. Only simple assumptions are made to the implementation of this work; the effect of packet loss is assumed to appear as the loss of 8×8 blocks. The missing regions appear as combinations of the missing blocks. During each recovery effort, the proposed method tries to recover a single block, inattentive to the overall shape of the lost region(s). Also, the position of lost blocks is assumed to be known. Such information is readily available through error control coding of packets sent over the network. The algorithm is developed for grav level still images, but it can easily be generalized for color image or video applications.

The rest of this paper is organized as follows. Section II introduces the SBRM algorithm. The implementation results for high error rate conditions are included in section III, and the concluding remarks are made in section IV.

2. THE PROPOSED METHOD

To recover a missed block, the SBRM selects another block of the same size within the image, so that two blocks are the most similar in range. In fact, each block of the image is identified by its enclosing frame; if two frames are similar, then their interior blocks are also recognized as similar, so that they can be replaced by each other. During the recovery procedure, SBRM searches for not only intact blocks, but also the blocks which may contain missed pixels. The algorithm iterates until all missed pixels are filled by appropriate substitutes.

To this end, the SBRM divides the image into nonoverlapping blocks. A block is a *corrupt* if it contains any number of lost pixels. Corresponding to each block, the algorithm takes an encompassing $M \times M$ block, which is called the *range block* (Fig. 1). To evaluate the *range similarity* of two blocks, the difference between their corresponding range blocks is computed in MSE sense.

The reliability of each pixel is indicated by a value of the range 0 to 1 stored in a *table of merit* that is updated during the recovery process as follows. The table of merit is initialized by allocating 0 to the lost pixels, and 1 to the intact received pixels. Since the recovery process relies on previously recovered pixels, the reliability of newly recovered pixels decreases as the algorithm proceeds, so the *merit* of a recovered pixel is evaluated as a decreasing function of the iteration number. The table of merit is



Fig.1. Top: Structure of the target and the best match blocks. Bottom Left: Commonly available parts of ranges which are compared to evaluate the difference. Bottom Right: The recovered block.

employed to assess the reliability of the best matching measurement, as it is clarified in the next subsection.

During an iteration of the algorithm, each corrupt gets one chance to be recovered; the algorithm scans the image to find corrupts, and wherever one is found, SBRM considers it as a *target* and applies the *basic procedure* on it. The basic procedure searches within a *searching area* that is a macroblock which encompasses the target, and looks for the block of the same size as the corrupt which complies with the best range matching.

After performing this procedure, the target may still contain lost pixels that can be recovered in the nest iteration(s) of the algorithm. The basic procedure also updates the table of merit, so that the corresponding merits of the newly restored pixels are set. In the very following subsection, the basic recovery procedure is introduced. Afterwards, the general algorithm is represented, which iteratively employs the basic procedure.

2.1. Basic Procedure

Let **x** denotes the vector in which the pixel values of an $N \times N$ target block are vectorized, so that the values of the unavailable pixels are set to 0,

$$\mathbf{x} = \begin{bmatrix} x_i \end{bmatrix}_{N^2 \times 1}, \quad x_i = \begin{cases} pixel \ value, \ \text{if available} \\ 0, \qquad \text{if lost} \end{cases}.$$
(1)

Similarly, the range vector \mathbf{r}^{x} is the vectorization of the corresponding $M \times M$ range block, (M > N)

$$\mathbf{r}^{x} = \left[r_{i}^{x} \right]_{M^{2} \times 1}, \ r_{i}^{x} = \begin{cases} pixel \ value, \ \text{if available} \\ 0, \qquad \text{if lost} \end{cases}.$$
 (2)

The merit vector \mathbf{m}^x includes the values from the table of merit which correspond to the pixels of \mathbf{r}^x . Also, the searching area is a macroblock of the size $A \times A$ which encompasses the target block. (Fig.1)



Fig. 2. Eight different scanning orientations.

Let \mathbf{S}^x denote the *selecting matrix* of \mathbf{r}^x , which is an $M^2 \times M^2$ diagonal matrix so that,

$$\mathbf{S}^{x} = \begin{bmatrix} s_{i,j}^{x} \end{bmatrix}, \ s_{i,j}^{x} = \begin{cases} 1, \text{ if } i = j \& r_{i}^{x} \text{ is available} \\ 0, \text{ otherwise} \end{cases}.$$
 (3)

The basic procedure forms a set Λ of all feasible $N \times N$ blocks within the searching area, except for the target block, in which each $\mathbf{y}_k \in \Lambda$ is set in the same way as (1) and contains at least one intact received or previously recovered pixel that is located in the lost part of \mathbf{x} . The last condition guarantees that during each iteration, at least one pixel of the target is filled, so that all lost pixels are recovered eventually. The range vector \mathbf{r}_k^{y} , the merit vector \mathbf{m}_k^{y} , and the selection matrix \mathbf{S}_k^{y} are also defined for each \mathbf{y}_k , as the same as for \mathbf{x} .

Let vector \mathbf{d}_k indicate the difference between commonly available pixels of \mathbf{r}^x and \mathbf{r}_k^y , (Fig.1) that is

$$\mathbf{d}_{k} = \mathbf{S}^{x} \mathbf{S}^{y} (\mathbf{r}^{x} - \mathbf{r}_{k}^{y}).$$
⁽⁴⁾

The *primary* MSE of \mathbf{r}_{k}^{y} is calculated by (5).

$$e_k = \frac{1}{nz\left(\mathbf{S}^x \mathbf{S}^y\right)} \sum_{i=1}^{M^2} d_{k,i}^2 , \qquad (5)$$

where $nz(\cdot)$ stands for the number of non-zero elements of the argument. If $nz(\mathbf{S}^{\mathbf{x}}\mathbf{S}^{\mathbf{y}}) = 0$ then \mathbf{y}_{k} is discarded.

The selection of best matching block is performed according to the *appraised* MSE e' s (6).

$$e'_{k} = w_{k}e_{k} + (1 - w_{k})\max_{\text{over }\Lambda} \{e_{k}\}, \qquad (6)$$

where w_k is the weighting factor that normalizes MSE (7).

$$w_{k} = \mathbf{m}^{x \mathrm{T}} \cdot \mathbf{m}_{k}^{y} / nz \left(\mathbf{S}^{x} \mathbf{S}^{y} \right)$$
⁽⁷⁾

where the symbols T and \cdot stand for transpose and inner product operations, respectively. In this manner, as the mutual merit of compared pixels increases, the primary MSE becomes more reliable and when the mutual merit of compared pixels is low for a temporarily examined \mathbf{y}_k , the basic procedure reduces the chance of its selection by leading the corresponding appraised MSE to the maximum MSE in the searching area.

The *best range matching* \mathbf{y}^* is a member of Λ which satisfies the minimum appraised MSE criterion, (8).

$$\mathbf{y}^* = \mathbf{y}_k, \text{ so that } e_k = \min_{\text{over } \Lambda} \left\{ e_l \right\}$$
(8)

The available pixels of \mathbf{y}^* are utilized to fill the lost pixels of \mathbf{x} , that is the pixels of merit 0,

$$\mathbf{x}_{new} = \begin{bmatrix} x_{new,i} \end{bmatrix}, \ x_{new,i} = \begin{cases} y_i, \text{ if } x_i \text{ is lost } \& y_i \text{ is available} \\ x_i, \text{ otherwise} \end{cases}$$
(9)

Finally, the basic procedure updates the table of merit by setting the merit of newly recovered pixels. (10)

$$\mathbf{m}_{new}^{x} = \left[m_{new,i} \right], \ m_{new,i} = \begin{cases} f(t), \ \text{if } x_i \text{ is just recovered} \\ m_i, \text{ otherwise} \end{cases}, (10)$$

where t indicates the iteration number of general algorithm, and $f(\cdot)$ is a decreasing function of the argument.

2.2. General Algorithm

In each of iterations, the whole image is scanned in conventional raster scanning order. The basic procedure is applied *once* to recover each corrupted block. The rest of lost pixels are left to be recovered in next iterations(s). This procedure is repeated until all lost pixels are recovered.

Since the best range matching process depends on previously recovered pixels, different scanning orientations result in different error propagation patterns which affect the performance of recovery [2]. To alleviate the effect of choosing a specific scanning order, the general algorithm just described is performed for eight different scanning orders, (Fig. 2). The final recovery result is then computed by averaging the results of these eight runs.

3. EXPERIMENTAL RESULTS

The proposed method has been tested on grayscale images of Lena and Barbara over a broad range of block loss ratios and for block, range and searching area sizes of N = 8, M = 10 and $A = 3N \times 3N$, respectively. The choice of N is in similar with the partitioning size used in some popular compression standards such as JPEG. The size of range is identical to [1]. Our tests show that larger range blocks and searching areas do not necessarily improve the performance of SBRM in high loss conditions. Besides, it affects the computational simplicity of the algorithm.

The PSNR evaluation of the recovered Lena is reported in Fig. 3, as compared to the existing EC methods in high packet loss ratios. The results for Barbara (Fig. 4 and Fig. 5) show the power of the proposed method in recovery of textures.

4. CONCLUSION AND DISCUSSION

A sequential error concealment method based on the spatial similarities within the image is proposed in this paper and its power in recovering lost textures is shown to outperform the existing methods in high packet loss conditions. The main advantage of the proposed method is its simplicity of implementation, that is, it does not utilize computationally expensive processes to determine similarities within the image. It should be considered that good PNSR results do not necessarily guarantee the performance of an error concealment method. The reconstructed image should be subjectively reasonable to the human vision system. It is perceptible that, beside the good PSNR, SBRM exclusively promises the perceptual fidelity of reconstruction.

Our results can be improved by application of an additional denoising procedure. Besides, since no restricting condition is imposed, the proposed method can be readily extended for color image or video, if computational issues are addressed.

5. REFERENCES

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Fig. 3. Performance of SBRM on Lena, a comparison to: Watermarkingbased BNM [7], Watermarking with subbands [8] and Hybrid EC [9].



Fig. 4. Left: Corrupted Barbara, PSNR= 8.89 dB, with 50% consecutive block loss. Right: Recovered Barbara by SBRM, PSNR= 28.35 dB.



Fig. 5. A close-up view of the performance of SBRM, Right: Corrupted. Left: Recovered. Top: 20% block loss, Bottom: 80% block loss.