SUBIMAGE ERROR CONCEALMENT TECHNIQUES

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ABSTRACT

Images transmitted via ATM networks suffer from quality degradation due to buffer overflow or cell header errors which cause ATM cells to be lost. This paper presents a new approach to conceal the errors in the received images by the application of novel error recovery techniques to the decomposed DCT-coefficient subimages of the corrupted image. These techniques were developed to recover images corrupted by impulsive noise. Since decomposing the corrupted image into the DCT-coefficient subimages generates low resolution images corrupted by impulsive noise, all the techniques used to recover images corrupted by impulsive noise can be used to recover the subimages and hence the corrupted image. In this paper, we study the performance of different iterative and non-linear techniques to recover the corrupted subimages. The quality of the recovered image using these techniques is better than the quality obtained by many classical error concealment techniques.

1. INTRODUCTION

Due to the limited capacity of the ATM buffers, low priority cells are discarded whenever an overflow occurs in the buffers. Since the loss of ATM cells causes the corruption of the corresponding blocks of the image, it is a common procedure to declare any corrupted block as a lost block and discard all the correctly received data for that block. This leaves the corrupted image with empty blocks at the locations of the corrupted ones. Many techniques have been proposed to conceal the erroneous blocks in the damaged image. Some techniques are related to the *Projection Onto Convex Sets (POCS)* method [1]. Other techniques implement various spatial interpolation [2] and temporal extrapolation [3] methods. The idea of using subband decomposition in the error concealment process was used in [4, 5] to interpolate the missing subband coefficients. In this paper, we present a new technique in which the corrupted image is converted into a set of subimages which can be considered as small images corrupted by impulsive noise. Errors in these images can be concealed by the application of an iterative or a non-linear technique designed for such type of corrupted images. The organization of the paper is as follows: In section 2, we present the iterative and non-linear techniques used to recover the errors in the corrupted subimages. Section 3 presents the proposed algorithms. A comprehensive discussion of the obtained results with a performance comparison- in terms of the signal-to-noise ratio (SNR)- among the different variations of the proposed technique and some other classical techniques is presented in section 4. Finally, a summary and some conclusions are presented in section 5 of the paper.

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2. ITERATIVE & NON-LINEAR ERROR RECOVERY TECHNIQUES

Non-uniform sampling theory has played an important role in the development of many error recovery techniques for speech and image signals [6, 7]. Any discrete signal with lost samples can be considered as a non-uniformly spaced signal and the values of the lost samples can be recovered if certain constraints on the average sampling rate are met. Some recovery techniques implement error reduction methods iteratively [6, 7]. In the following subsections, we present two techniques dependent on the non-uniform sampling theory which are used in our algorithm to recover the missing DCT coefficients.

2.1. The Iterative Technique

This technique relies on the method of error reduction to improve the signal-to-noise ratio of the corrupted image. Each iteration in this technique improves the SNR of the recovered image if the average sampling rate is greater than or equal to the Nyquist rate [8]. Fig. 1 presents a block diagram of the iterative technique. In Fig. 1, $x[i,j]$ is the corrupted image, S is a non-uniform

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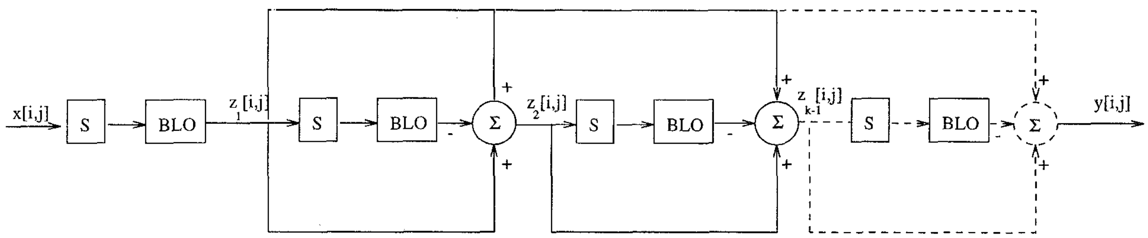

Figure 1: The Iterative Error Recovery Technique.

sampling operator and *BLO* is a *BandLimiting Operator* which can be as simple as a lowpass or a bandpass filter. It is shown in [8] that after k iterations to recover Poisson or uniformly-distributed samples, the SNR of the recovered image is:

$$SNR_k = k \cdot SNR_1 \tag{1}$$

where SNR_k is the SNR (in dBs) of the recovered image after the k^{th} iteration and SNR_1 is the SNR of the image after running the first iteration.

2.2. The Non-linear Technique

In this technique [9], a one-step, nonlinear operation is carried out to achieve similar SNRs to the iterative technique. This technique depends on analyzing the spectral content of the lowpass version of the corrupted image and the lowpass version of the nonuniform sampling image. The nonuniform sampling image is composed of unit impulses, $\delta[i - i_m, j - j_m]$, at the good pixel locations, $[i_m, j_m]$. Such image is created by thresholding the corrupted image and then hard limiting the thresholded version. A schematic diagram of the non-linear technique is shown in Fig. 2.

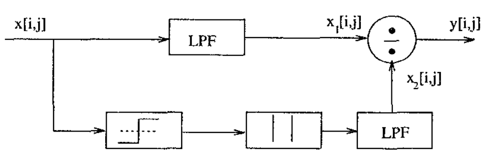

Figure 2: The Non-linear Division Error Recovery Technique.

3. THE ERROR CONCEALMENT ALGORITHM

The proposed algorithm makes use of the above two error recovery techniques to recover errors in the generated subimages of the corrupted image. When an ATM cell is lost, the whole corresponding block is declared to be lost by ignoring the rest of the correctly received block data and replacing all the block pixels with zeros. The above recovery techniques are not suitable to recover bursts of errors hence they can not be used directly to recover the lost blocks. By converting the image to its equivalent subimages, the above iterative and non-linear techniques can be used to conceal the errors in these subimages and hence recover the original image.

3.1. Subimage Decomposition

Many techniques have been developed to decompose images into their subbands. In our technique, we decompose the image into DCT subimages with equal resolutions. This is done by obtaining the 8×8 DCT transform of the original corrupted image. The resulting DCT coefficients of each block are then grouped together to form 64 subimages. For example, the DC coefficients of each block are grouped to form the first subimage, then the first AC coefficient (AC1) of each block is used to form the second subimage taking into consideration that the relative spatial location of each DCT coefficient is preserved in these subimages. For an $N \times N$ image decomposed using an 8×8 DCT block, the final output of the decomposition process is a set of 64 subimages with $\frac{N}{8} \times \frac{N}{8}$ dimensions. A general block diagram of the proposed algorithm is shown in Fig. 3.

3.2. The Subimage Iterative Technique

The simplest variation of the proposed technique is to apply the iterative technique directly to the decomposed subimages. In the iterative technique, the BLO which is used to filter the input subimages at each stage is designed to adapt to the spectral shape of the filtered subimage. To generate the 2-D mask of this filter (BLO), a copy of the FFT-transformed subimage is normalized and thresholded to eliminate any noise or unnecessary frequency components. This generates a variable mask for the filter which is dependent on the subimage to be filtered.

After concealing the errors in each subimage individually, the recovered subimages are recombined and then inverse-DCT transformed to yield the recovered image. For the results presented in this paper, we conceal the

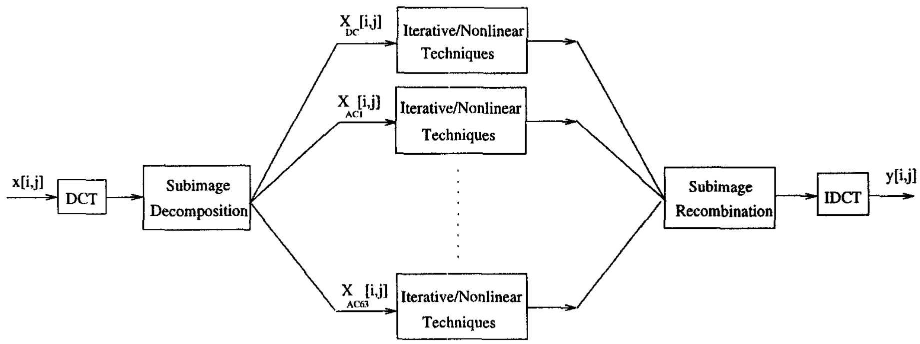

Figure 3: A general block diagram of the subimage error concealment technique.

errors in the first 6 subimages (the DC subimage and the first five AC subimages) since most of the energy is concentrated in these subimages.

3.3. The Iterative with Overhead Technique

In the *Iterative* technique, instead of generating the filter mask for each subimage, the exact masks can be sent as a protected side information to the destination node. In this method, the filter envelope shape and bandwidth for each of the first 6 subimages are packed as guaranteed cells and sent to the destination node. This side information is used by the BLO block in the *Iterative* technique to generate the proper filter masks to filter the corresponding subimages. Although the side information in this technique produces about 8% overhead, it improves the SNR of the recovered image by more than 1 *dB*.

3.4. The Subimage Non-linear Technique

The "*Iterative/Nonlinear Techniques* " block in Fig. 3 is replaced by the non-linear division block in this technique. This technique is supposed to converge to the recovered image in one step without iterations. Note that in Fig. 2, the lowpass filters in the upper and lower branches of this technique have the same bandwidth and spectral characteristics. Also, this technique assumes that the subimages are bandlimited which is almost the case for most of the subimages. Due to the negligible effect of considering the high frequency subimages, the first 6 subimages are only considered in the recovery process.

4. EXPERIMENTAL RESULTS

In this section, we report the results obtained by running the proposed iterative and nonlinear techniques to recover the errors encountered in the standard *Lenna* JPEG-coded image. All the results are reported for 256×256 *Lenna* image coded using the standard JPEG algorithm. To simulate the loss incurred in this image when transmitted via an ATM network, we considered the whole ATM network as a discrete channel since we are dealing with losses of discrete cells rather than losses in continuous waveforms. By varying the *Cell*

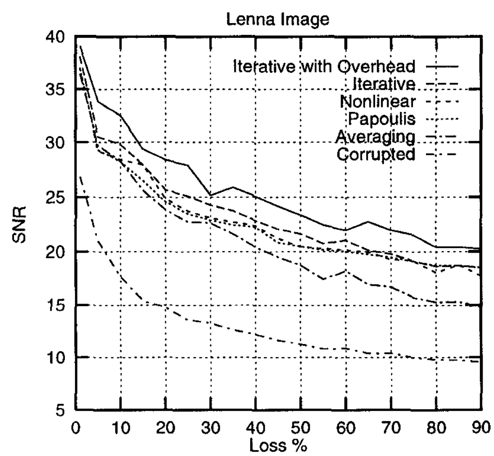

Figure 4: SNR vs. Loss % for the Iterative, Nonlinear and Iterative with Overhead techniques - 25 iterations.

Loss percentage from 1% to 90% for Lenna image, it can be seen from Fig. 4 that the *Iterative with Overhead* technique gives the best *SNR*. As expected, the *SNR* of the recovered image decreases with the percentage of cell loss increase. The *Iterative with Overhead* technique achieves at least 13 *dB* improvement in the *SNR* for the whole range of the cell loss percentages. It is also obvious that the *Iterative with Overhead* technique gives better *SNR* measures than the *Subimage Iterative* technique for all cell loss percentages. This is expected due to the fact that the overhead sent- which does not exceed 8% of the original coded bit stream- consists of information about the spectral properties of the original image. The *Non-*

linear technique performance is slightly better than that of *Papoulis-Gerchberg* technique [10, 11] and much better than the *Averaging* technique performance especially for high cell losses. In Fig. 5, we present the

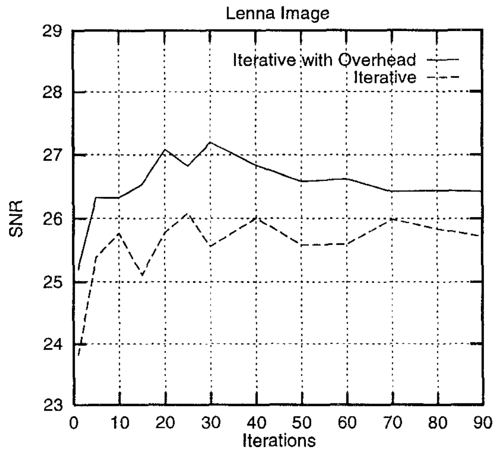

Figure 5: SNR vs. No. of Iterations for different variations of the Iterative technique - 20% cell loss.

results of running the iterative techniques for different numbers of iterations using the first 6 subimages and for 20% cell loss. It can be seen from the figure that for all the iterative techniques, the *SNR* increases with the increase in the number of iterations used to process the corrupted subimages till it reaches the maximum then it starts oscillating without any significant improvement.

4.1. Comparison with the Classical Methods

From the above discussion, it is apparent that most of the variations of the proposed technique give better *SNR* performance than the classical techniques such as *Papoulis-Gerchberg* and the *Averaging* techniques. The *Iterative with Overhead* technique, which can be considered as the best among the other techniques, gives an average *SNR* improvement of about 2.7 *dB* over the performance of *Papoulis-Gerchberg* technique and 5.5 *dB* over that of the *Averaging technique.*

5. CONCLUSION

Subimage iterative and non-linear techniques were presented and tested in this paper to conceal the errors in an error-prone environment. These techniques rely on the idea of decomposing the corrupted image into subimages which can be considered as images corrupted by impulsive noise. We used iterative and non-linear operations in the concealment process with and without sending overhead information. Most of these techniques give better *SNR* performance than many of the classical techniques even for very high rates of cell loss. These techniques are suitable for any error-prone environment such as the ATM and the wireless ATM where a high percentage of cells is expected to be lost.

6. REFERENCES

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