Locally adaptive passive error concealment for wavelet coded images

Joost Rombaut, Aleksandra Pižurica and Wilfried Philips

***Abstract*— This paper presents a novel locally adaptive error concealment method for subband coded images. For each lost low frequency coefficient, we estimate the optimal interpolation weights from its neighborhood. The calculation of the interpolation weights is optimized in the mean squared error sense, and takes into account the errors that would arise by horizontally and vertically interpolating the available neighbors of the lost coefficient. Compared to methods of similar complexity, the proposed scheme estimates the lost coefficients more accurately: on average, the PSNR is increased by up to 4.5 dB. The reconstructed images also look better and our method is fast and of low complexity.**

***Index Terms*— Image reconstruction, image communication, error concealment, wavelet coding.**

I. Introduction

In lossy packet networks such as the Internet, packets can be dropped, e.g., in case of network congestion. This data loss is particularly annoying for compressed data, as the loss of a single bit can make the rest of the data stream unusable. These problems are typically solved by protecting the data (e.g., forward error correction) or by implementing a protocol for resending lost packets. A good overview of the corresponding *Active Error Concealment* techniques, is given in [1]. In certain applications, packet retransmission is not an option, either because it is too slow (e.g., for real time video) or because there is no return channel (e.g., broadcasting). In these cases, *Passive Error Concealment* is essential.

In video applications, passive error concealment [1] exploits the remaining redundancy in images: missing pixel values (or pixel blocks) are *estimated* from the correctly received *neighboring* pixels (or blocks). To ensure maximal availability of correctly received neighbors, spatially adjacent pixels (or blocks) must be spread over different packets. This is called dispersive packetization. Our method requires a dispersive packetization scheme, but it is not restricted to any particular scheme. In this paper, we employ the minimax packetization of [2].

In this letter, we focus on error concealment for wavelet coded images. We compress images by dispersively spreading neighboring wavelet coefficients over different packets, and by coding these packets independently from each other with the coder of [2]. Then we simulate the loss of coded packets. In reality, if a packet gets lost during the transmission, the missing data are typically replaced by zeros, which results in annoying black holes in the received image. In our simulations, we recover the underlying image by an adaptive interpolation of the lost coefficients.

Compared to more common block-based approaches, relatively few passive concealment methods were reported for wavelet coded images. The existing methods are mainly traditional error concealment algorithms from the image domain which are slightly adapted for the reconstruction of lost low frequency coefficients. E.g., bilinear interpolation (the lost coefficient is replaced by the average of its four adjacent neighbors) has proved very efficient despite its simplicity [2]. The results are quite good in smooth areas but artifacts arise near edges and other discontinuities. In [3], a bicubic interpolation method is proposed. Correct edge placement is achieved by adapting the interpolation grid in horizontal and/or vertical direction according to the high frequency content. This method yields better results than bilinear interpolation, but is also more complex and slower which may be less suited for low-end video clients such as portable devices with only limited processing power. The method in [3] was only tested on uncompressed images and not in a realistic compression scenario. In [4], a Maximum A Posteriori (MAP) approach was applied using a Markov random field prior in each subband. This technique is highly performant but also computationally expensive. Other recent approaches are the block based techniques of [5] and [6]. The approach of [5] is very different from ours, because it recovers complete blocks of wavelet coefficients (for block based wavelet coders such as JPEG2000) simultaneously, while we consider (more or less) isolated lost coefficients because of the dispersive packetization. Traditional error concealment algorithms such as [6] also recover complete pixel blocks for block based image coders such as JPEG and JPEG2000, and are also not applicable in a dispersive packetization context.

In this letter, we propose a novel and fast locally adaptive interpolation scheme. The complexity of our method is similar to that of bilinear interpolation but the reconstruction quality is much better. The method is an improvement of our earlier related scheme [7] which is efficient, but rather heuristic with experimental parameter optimization and with incomplete reconstruction of the subbands. In this letter, we optimize the parameters in the mean squares sense and process *all* subbands, which allows an important quality improvement over the results reported in [7] at the expense of a minor increase in processing time. The results demonstrate a significant improvement over the best available adaptive MAP approach

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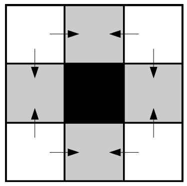

Fig. 1. The proposed concept. A lost coefficient (black square) is interpolated from its nearest neighbors (grey squares). The horizontal and vertical interpolation weights are calculated from the errors made by interpolating these nearest neighbors in the corresponding directions (marked by arrows).

of [4]. The new method is much less complex than [4] and yields results that are better in terms of mean squared error and visually.

In the next section, we explain the proposed interpolation method, and we also present its iterative extension. Results and findings are in Section III, and conclusions in Section IV.

II. The proposed concealment method

The proposed method focuses on wavelet coded images but is applicable to all multiresolution codecs (such as bandelets, contourlets, etc.). For optimal error concealment, the recovery of the lost low-frequency coefficients (i.e., scaling coefficients) is essential and our method concentrates on that problem.

The loss of high frequency coefficients has much less impact on the visual quality and we recover them with one dimensional linear interpolation as in [2], [3]; we set lost coefficients in diagonal subbands to zero.

The proposed method for low frequency coefficients could be extended to the high frequency subbands, but because these subbands benefit greatly from directional interpolation, we would need to adapt the scheme to take into account the preferential interpolation direction. This would increase the complexity, while we assume that it would yield only modest gains in image quality.

In the following, we focus on the reconstruction of lost scaling coefficients. A scaling coefficient at position (i,j) will be denoted by $S_{i,j}$.

The aim of the proposed approach is to estimate the locally optimal interpolation *direction* from the correctly received neighboring coefficients, and to adapt the interpolation weights accordingly. The main idea is to estimate the interpolation errors in different directions by measuring errors that arise from interpolating nearest *correctly received* neighbors in the corresponding directions (see Fig. 1). These measurements are built in a minimum mean square error parameter optimization procedure.

Let $\widehat{S}^H_{i,j}$ and $\widehat{S}^V_{i,j}$ denote the estimates of the coefficient $S_{i,j}$ by respectively horizontal and vertical linear interpolation. We denote the corresponding interpolation errors as $e^H_{i,j}$ and $e^V_{i,j}$ such that:

$$\begin{cases} \widehat{S}^H_{i,j} &= (S_{i,j-1} + S_{i,j+1})/2 = S_{i,j} + e^H_{i,j}, \\ \widehat{S}^V_{i,j} &= (S_{i-1,j} + S_{i+1,j})/2 = S_{i,j} + e^V_{i,j}. \end{cases} \tag{1}$$

We assume that $E(e^H_{i,j}) = 0$ and $E(e^V_{i,j}) = 0$, and we denote the local variances of the interpolation errors by: ${\sigma^H_{i,j}}^2 = E\left[\left(e^H_{i,j} - E(e^H_{i,j})\right)^2\right] = E\left[\left(e^H_{i,j}\right)^2\right]$, and ${\sigma^V_{i,j}}^2 = E\left[\left(e^V_{i,j}\right)^2\right]$. We estimate the lost coefficient $S_{i,j}$ by a weighted average of $\widehat{S}^H_{i,j}$ and $\widehat{S}^V_{i,j}$:

$$\widehat{S}_{i,j} = \alpha^V_{i,j}\widehat{S}^V_{i,j} + \alpha^H_{i,j}\widehat{S}^H_{i,j}, \tag{2}$$

with $\alpha^V_{i,j} + \alpha^H_{i,j} = 1$, and we choose the interpolation weights $\alpha^V_{i,j}$ and $\alpha^H_{i,j}$ such that the interpolation error is minimal:

$$\begin{aligned} \alpha^H_{i,j} &= \arg_{\alpha^H_{i,j}} \min\left\{E\left[(\widehat{S}_{i,j} - S_{i,j})^2\right]\right\} \\ &= \arg_{\alpha^H_{i,j}} \min\left\{E\left[(\alpha^H_{i,j}\widehat{S}^H_{i,j} + (1-\alpha^H_{i,j})\widehat{S}^V_{i,j} - S_{i,j})^2\right]\right\} \\ &= \arg_{\alpha^H_{i,j}} \min\Big\{E\left({\alpha^H_{i,j}}^2 {e^H_{i,j}}^2\right) + E\left({e^V_{i,j}}^2\right) + \\ &\quad E\left({\alpha^H_{i,j}}^2 {e^V_{i,j}}^2\right) + 2E\left(\alpha^H_{i,j} e^H_{i,j} e^V_{i,j}\right) - \\ &\quad 2E\left({\alpha^H_{i,j}}^2 e^H_{i,j} e^V_{i,j}\right) - 2E\left({e^V_{i,j}}^2 \alpha^H_{i,j}\right)\Big\}. \end{aligned}$$

Assuming that $e^H_{i,j}$ and $e^V_{i,j}$ are approximately uncorrelated, $E\left(e^H_{i,j}e^V_{i,j}\right) = 0$, we find:

$$\begin{aligned} \alpha^H_{i,j} &= \arg_{\alpha^H_{i,j}} \min\left\{{\alpha^H_{i,j}}^2\left({\sigma^H_{i,j}}^2 + {\sigma^V_{i,j}}^2\right) - 2\alpha^H_{i,j}{\sigma^V_{i,j}}^2 + {\sigma^V_{i,j}}^2\right\} \\ &= {\sigma^V_{i,j}}^2 / \left({\sigma^H_{i,j}}^2 + {\sigma^V_{i,j}}^2\right), \end{aligned} \tag{3}$$

and from $\alpha^V_{i,j} = 1 - \alpha^H_{i,j}$, we have

$$\alpha^V_{i,j} = {\sigma^H_{i,j}}^2 / \left({\sigma^H_{i,j}}^2 + {\sigma^V_{i,j}}^2\right). \tag{4}$$

We estimate the variance ${\sigma^H_{i,j}}^2 = E\left[\left(e^H_{i,j}\right)^2\right]$ and ${\sigma^V_{i,j}}^2 = E\left[\left(e^V_{i,j}\right)^2\right]$ at each spatial position (i,j) from the available measurements on the nearest correctly received neighbors:

$$\begin{aligned} {\sigma^H_{i,j}}^2 &= \left({e^H_{i-1,j}}^2 + {e^H_{i+1,j}}^2\right)/2 \\ &= \left((S_{i-1,j} - \widehat{S}^H_{i-1,j})^2 + (S_{i+1,j} - \widehat{S}^H_{i+1,j})^2\right)/2, \end{aligned}$$

$$\begin{aligned} {\sigma^V_{i,j}}^2 &= \left({e^V_{i,j-1}}^2 + {e^V_{i,j+1}}^2\right)/2 \\ &= \left((S_{i,j-1} - \widehat{S}^V_{i,j-1})^2 + (S_{i,j+1} - \widehat{S}^V_{i,j+1})^2\right)/2. \end{aligned}$$

If $\sigma^H_{i,j} = \sigma^V_{i,j} = 0$, then we choose $\alpha^H_{i,j} = \alpha^V_{i,j} = 1/2$.

In the bilinear interpolation method and in the proposed method, a lost coefficient is interpolated from its four nearest neighbors. Therefore, if a neighbor of a lost coefficient is also missing, this has an impact on its reconstruction. Although the dispersive packetization minimizes the probability that coefficients adjacent to a lost coefficient are also lost [2], this situation can still occur, especially at high packet loss rates.

Since in the proposed method, the interpolation weights are estimated from the surrounding coefficients, loss of any of these adjacent coefficients decreases the reliability of the estimated interpolation weights. A solution for this problem is iteratively recalculating the optimal weights and the lost coefficients. Initially, the lost coefficients are estimated with the bilinear interpolation scheme which uses the available neighbors. In a second iteration, the interpolation weights $\alpha^H_{i,j}$ and $\alpha^V_{i,j}$ take into account estimated lost coefficients of the first iteration. This process can be iterated a number of times. In this case, quality improvement comes at the expense of a higher computational cost.

TABLE I

AVERAGE PSNR [dB] FOR: BILINEAR INTERPOLATION (BI), THE ADAPTIVE MAP APPROACH [4] AND THE PROPOSED METHOD, FOR p LOST PACKETS

Lena (0.21 bpp)			
p	BI	MAP [4]	Proposed
0	32.18	32.18	32.18
1	28.80	29.05	29.07
2	26.81	27.14	27.16
3	25.35	25.71	25.75
4	24.15	24.55	24.58

Couple (0.84 bpp)			
p	BI	MAP [4]	Proposed
0	33.33	33.33	33.33
1	30.27	29.94	30.50
2	28.38	27.94	28.66
3	26.95	26.49	27.26
4	25.74	25.33	26.11

Tweety (0.84 bpp)			
p	BI	MAP [4]	Proposed
0	45.95	45.95	45.95
1	36.21	39.61	40.66
2	33.19	36.43	37.59
3	31.13	33.93	35.13
4	29.40	31.79	32.97

III. RESULTS

Typical packet loss rates in the Internet, without retransmission, are in the range of 2% to 10% [1]. As data packet loss is typically bursty in nature, the instantaneous packet loss rate can be much higher. We tested the proposed interpolation method in a realistic scenario with both low and high packet loss rates, in an experiment similar to the one in [4]. We simulated the transmission of three test images, *Lena* (512×512), *Couple* (256×256), and *Tweety* (256×256), over a lossy packet network. The wavelet coefficients (calculated with the Daubechies 9/7 bi-orthogonal wavelet with four levels[1] of wavelet decomposition) of each image were stored in 16 packets using the dispersive packetization strategy of [2]. By using dispersive packetization, we avoid the possibility that all neighbors of a lost coefficient are also lost, if the number of lost packets p is equal to or smaller than 4. On average, the number of lost neighbors is minimized.

After packetization, each packet was coded independently of the other packets by using the coder of [2]. This guarantees independent decodability which is important for error recovery. We then simulated the loss of every combination of p packets for $p = 1, \ldots, 4$. For $p = 1, \ldots, 4$, there are respectively 16, 120, 560 and 1820 possible combinations. The lost low frequency coefficients were repaired using three reconstruction methods: bilinear interpolation as in [2], the adaptive MAP approach of [4], and the proposed locally adaptive method. For each p, we calculated the average PSNR of the reconstructed images for each reconstruction method. The results of this experiment are given in Table I.

If no packets are lost, the PSNR of the reconstructed image is equal to the PSNR of the broadcasted compressed image. For *Lena* (compressed at 0.21 bpp), the PSNR of the compressed image is 32.18 dB. The PSNR of the compressed *Couple* and *Tweety* images (both 0.84 bpp) are respectively 33.33 dB and 45.95 dB. Note that, for each image, these compression ratios produce an average packet size of 430 Bytes, which is suitable for Internet transmission without fragmentation.

The results in Table I show that our proposed method outperforms bilinear interpolation by 0.2 dB up to 4.4 dB for low packet loss rates and by 0.4 dB up to 3.5 dB for high packet loss rates. For *Lena*, the average PSNR results of the new method are similar to those of the MAP approach of [4]. For the *Couple* and *Tweety* images, the proposed method outperforms [4] by 0.6 dB up to 1.0 dB for low packet loss rates and by 0.8 dB up to 1.2 dB for high packet loss rates. The experiment was repeated on other images (e.g., *Peppers*, *Boat*, *Barbara*), resulting in similar conclusions: for both low and high packet loss rates, our method always outperforms bilinear interpolation and the MAP approach of [4].

[1] We use four levels of wavelet decomposition as this provides the ideal trade off between compression ratio (which is close to optimal for four or more levels) and reconstruction quality (reconstruction of low frequency coefficients gives optimal results for four or fewer levels).

TABLE II

AVERAGE PSNR [dB] FOR THE PROPOSED METHOD FOR 2 AND 4 ITERATIONS

	Lena		*Couple*		*Tweety*	
p	$n = 2$	$n = 4$	$n = 2$	$n = 4$	$n = 2$	$n = 4$
0	32.18	32.18	33.33	33.33	45.95	45.95
1	29.07	29.07	30.50	30.50	40.66	40.66
2	27.19	27.18	28.68	28.68	38.02	38.11
3	25.81	25.82	27.31	27.32	36.02	36.32
4	24.68	24.72	26.19	26.21	34.19	34.81

The proposed method not only yields a higher PSNR than the adaptive MAP approach of [4], it is also considerably less complex. The method of [4] was reported to require 1540 additions and 1456 multiplications for each lost coefficient. Our new method requires only 14 additions and 13 multiplications for each lost coefficient, which is a reduction of a factor 100 compared to [4]. For comparison, the bilinear interpolation requires 3 additions and 1 multiplication.

The results for bilinear interpolation in Table I are higher than the corresponding ones in [4], because we processed all the levels of the decomposition to optimize the performance. The same was done for the other two methods.

In the previous experiment, each lost coefficient was reconstructed only once, and as a result, the loss of adjacent coefficients decreased the reconstruction quality as the estimates of $\alpha^H_{i,j}$ and $\alpha^V_{i,j}$ are not optimal when neighboring coefficients are lost. Table II shows the results for 2 and 4 iterations of our reconstruction method. For small packet loss rates, these iterations have little or no impact on the reconstruction quality of the proposed method. This is due to the dispersive packetization: lost coefficients are spread as far apart from each other as possible, so that there is little or no interference between their reconstruction. In this case, the first iteration will immediately calculate the optimal interpolation coefficients. For higher packet loss rates ($p > 1$), the iterative method produces a gain in PSNR but this gain is image dependent. For $p = 4$ and $n = 2$, there is an increase of 0.10 dB for *Lena*, 0.08 dB for *Couple*, and 1.22 dB for *Tweety* compared to the non-iterative approach from Table I. For $n = 4$, the gain is a little higher.

Note that n iterations of our proposed method need $14n$

Fig. 2. **(a)** The *Lena*-image compressed at 0.21 bpp (PSNR = 32.18 dB). **(b)** *Lena*-image after loss of packet 8. **(c)** Bilinear interpolation (PSNR = 28.35 dB). **(d)** Adaptive MAP approach [4] (PSNR = 28.92 dB). **(e)** The proposed method (PSNR = 28.86 dB).

additions and $13n$ multiplications, which is still negligible compared to the number of operations of the adaptive MAP approach of [4].

We also illustrate visual results for two images. Fig. 2 (a) is the *Lena*-image compressed at 0.208 bpp. Fig. 2 (b) is the image after the loss of packet 8 (i.e., 6.25% of the coefficients lost). Fig. 2 (c), (d) and (e) are the images after reconstruction with respectively bilinear interpolation as in [2], the adaptive MAP approach of [4] and the proposed reconstruction method. While [4] and the proposed method yield almost the same PSNR, the visual quality of our method is better.

In Fig. 3 we illustrate the results for the iterative version of the proposed method, with two iterations, for a high packet loss rate of 25%. Without reconstruction (Fig. 3 (b)), it is difficult to see the image content. The reconstructed image shows a clear improvement over [4] in terms of PSNR and visually.

IV. Conclusion

This letter presents a novel locally adaptive interpolation method for lost low frequency wavelet coefficients in image and video communication. Our method estimates the optimal interpolation weights from neighboring coefficients using

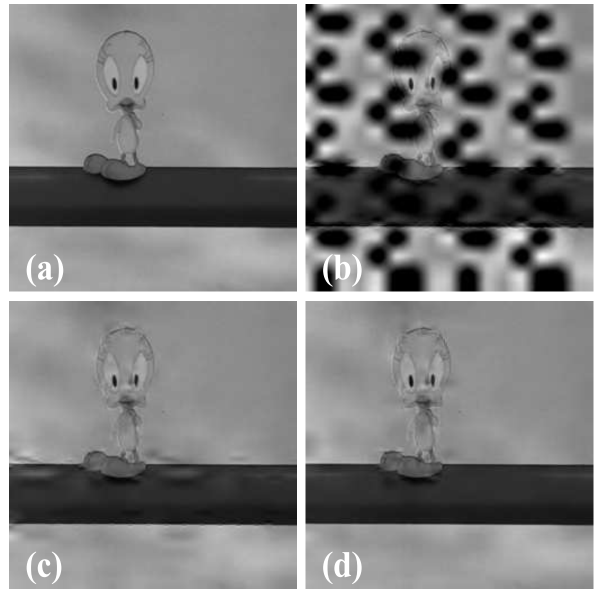

Fig. 3. **(a)** The *Tweety*-image compressed at 0.84 bpp (PSNR = 45.95 dB). **(b)** *Tweety*-image after loss of packets 1, 6, 7 and 14. **(c)** Reconstruction with the adaptive MAP approach of [4] (PSNR = 32.66 dB). **(d)** Iterative reconstruction with our proposed reconstruction method (PSNR = 35.07 dB).

novel error measures for horizontal and vertical interpolation, calculated from the neighbors of the lost coefficient. Experiments on different images have demonstrated a significant improvement over bilinear interpolation (up to 4.4 dB in case of 6.25% coefficients lost, and up to 3.5 dB in case of 25% loss) and over state-of-the-art methods.

An iterative version of the proposed method further increases its PSNR gain. While yielding a very good reconstruction quality, our interpolation method is of very low complexity.

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