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Model-Based Real-Time Progressive Transmission of Images over Noisy Channels

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***Abstract*— *Many unequal error protection algorithms used in image communication systems need the operational distortion-rate (D/R) curve of the source coder whose computation is time-consuming. We study the use of parametric models instead of the true D/R curves for wavelet-based embedded image and video coders. We propose a Weibull model and show its superiority to the previous models for real-time applications. For unequal error protection over binary symmetric and packet erasure channels, the Weibull model yielded performance similar to the one obtained with the true D/R curve while satisfying the real-time constraint.*

I. Introduction

Because of the increasing popularity of the Internet and wireless multimedia products, a lot of work has recently been dedicated to the design of efficient systems for the transmission of images and video over noisy channels. Traditional error control systems, which are based on error detection and retransmission, suffer from delays that may be unacceptable in real-time applications. An alternative is to use forward error correction (FEC). Some of the best FEC systems for multimedia data generate an embedded wavelet bitstream and protect it in an optimal way with unequal error protection [1], [2], [3], [4], [5], [6], [7], [8].

In this paper, we focus on the *real-time* ability of these FEC systems. The real-time constraint is important in wireless communications. For example, suppose that a user wants to take a picture with a digital camera of a 3G mobile phone and immediately send it to a receiver. The encoder must compress the image, protect the source code, and send the source-channel bitstream in real-time. Whereas the source coding with an appropriate embedded wavelet coder is very fast, the best unequal error protection algorithms require a time-consuming preprocessing step, which consists of computing the operational distortion-rate curve of the original image. Although an embedded coder has the desirable property that the source code at the highest available bitrate can be used to generate the distortion-rate points at all lower rates, the computation time is still prohibitive for real-time applications. One faster solution is to estimate the distortion-rate points in the wavelet domain during the encoding. This gives very good results for orthogonal or nearly orthogonal wavelet filters. Another solution is to use a parametric model instead of the true distortion-rate function. An important advantage of the model approach is that the encoder need not send overhead bits to specify the error protection solution to the receiver. Indeed, only the model parameters (a few real numbers) have to be transmitted, allowing the receiver to compute the solution on its side.

Mallat and Falzon [9] introduced a parametric model for wavelet-based coders but they did not discuss applications. This model was used by Huang and Liang [10] for joint-source channel coding with MPEG 2. A different parametric model for the distortion-rate function of the SPIHT coder [11] was used for joint-source channel coding by Appadwedula, Jones, Ramchandran, and Kosintzev [12]. However, in all these works the complexity aspects, which are essential in real-time applications, were not studied.

We propose a parametric Weibull model for the operational distortion-rate curves of the SPIHT, JPEG2000 [13], and 3D SPIHT [14] wavelet coders, which are the most popular embedded wavelet coders. We show that the Weibull model is more appropriate for real-time joint source-channel coding than the models of [9], [12]. We apply the parametric models to unequal error protection in binary symmetric and packet erasure channels and show that they allow the computation of a solution in real-time while ensuring reconstruction quality similar to the one obtained with the true distortion-rate function.

The rest of the paper is organized as follows. In Section II, we give an overview of unequal error protection algorithms of embedded codes in binary symmetric and packet erasure channels. In Section III, we propose a parametric model that approximates the operational distortion-rate function of the SPIHT, JPEG2000, and 3D SPIHT source coders and show its superiority over the previous models of [9], [12]. In Section IV, we present simulation results which show the relevance of a parametric model for real-time joint source-channel coding in binary symmetric and packet erasure channels.

II. Algorithms for error protection

A. Binary symmetric channels

One of the most successful systems for the robust progressive transmission of images over binary symmetric channels was introduced by Sherwood and Zeger [1]. The basic idea is to use an embedded wavelet coder as a source coder and a concatenation of an outer cyclic redundancy-check (CRC) coder and an inner rate-compatible punctured convolutional (RCPC) coder as a channel coder. Error propagation is avoided by stopping the decoding when the first packet error is detected. Similar systems were also efficiently used by Banister, Belzer, and Fischer [15] for protecting JPEG2000 [13] coded images and by Xiong, Kim, and Pearlman [16] for video transmission.

The fastest rate-distortion based unequal error protection algorithm for this system is the local search algorithm of Hamzaoui, Stanković, and Xiong [17]. The algorithm starts from a solution that maximizes the expected number of received source bits and iteratively searches for a solution with a lower expected distortion using the distortion-rate function of the source coder. Experimental results for a binary symmetric channel with the SPIHT coder and JPEG2000 show that the solution given by the algorithm is almost optimal [17].

B. Packet erasure channels

Systematic Reed-Solomon (RS) codes allow efficient packet loss protection of embedded bitstreams in packet erasure channels. The best RS-based unequal loss protection algorithms are due to Puri and Ramchandran [3] and Stanković, Hamzaoui, and Xiong [18]. The first algorithm computes the convex hull of the operational distortion-rate curve in a preprocessing step. The local search technique of [18] is similar to that of [17] and also needs the distortion-rate function of the source coder.

III. Modeling the distortion-rate function

The operational distortion-rate function of the source coder gives the reconstruction fidelity at a given source rate. The reconstruction fidelity is commonly measured by the mean-square error (MSE) or the peak signal-to-noise ratio (PSNR), which is defined in dB as

$$PSNR = 10 \log_{10} \frac{255^2}{MSE}. \quad (1)$$

All unequal error protection algorithms of the previous section require the operational distortion-rate curve of the source coder for the original image. To determine p distortion-rate points, one needs in principle p encodings and p decodings of the source coder. Since the source code is embedded, one encoding at the highest rate gives the bitstream at the $p-1$ lower rates. But p decodings are still required. Moreover, these algorithms work best under the ideal assumption that the operational distortion-rate curve is convex.

An alternative to the true distortion-rate function is a parametric model. Mallat and Falzon [9] proposed the model

$$y = Cr^{1-2\gamma}, \quad (2)$$

where C is a positive number and γ is of the order of 1, to approximate the MSE of a zerotree-based wavelet coder at bit rates r under 1 bit-per-pixel (bpp).

In [12], the operational MSE-rate function of the SPIHT coder was modeled by the sum of four exponential terms

$$y = \sum_{k=1}^{4} c_k e^{-l_k r}. \quad (3)$$

We show in the following that a better modeling can be obtained with a Weibull model

$$y = a - be^{-cr^d}, \quad (4)$$

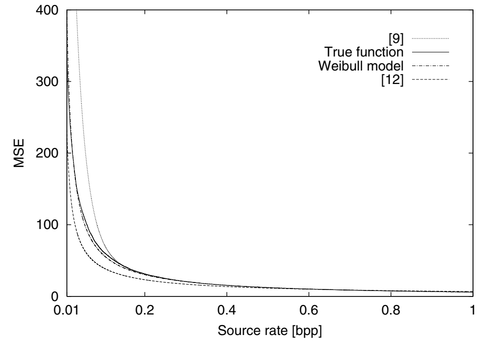

Fig. 1. Comparison between the Weibull model, the model of [9], and the model of [12] with the true MSE-rate function of the SPIHT coder for the 512 × 512 Lenna image.

where the real numbers a, b, c, and d are parameters that depend on the image and the source coder.

Suppose that we are given N MSE-rate points $(r_i, MSE(r_i))$, $1 \leq i \leq N$, corresponding to N equidistant rates in the range $[0.001, R]$. To fit these points to the above models, we used linear least squares (applied to the points $(\log r_i, \log MSE(r_i))$, $i = 1, \ldots, N$) for (2) and the Levenberg-Marquardt nonlinear regression method [19] for (3) and (4).

In the paper, we give numerical results for the standard 8 bpp 512 × 512 Lenna image. We obtained similar results for other images.

For the SPIHT source coder, a maximum source rate R of 1 bpp, and $N = 1024$ data points, the root-mean square (rms) of the difference in MSE between the models and the true MSE-rate function was 107.99, 1.11, and 3.07 for (2), (3), and (4) respectively. For JPEG2000 and the same settings, the rms error was 121.39, 32.95, and 29.7 for (2), (3), and (4) respectively.

These results may indicate that (3) and (4) should be preferred to (2). However, the relevance of a parametric model for our real-time unequal error protection problem depends not only on the accuracy of the data fitting but also on both the number N of data points used for the fitting and the number of parameters in a model. The number of parameters should be kept small because both the size of the overhead and the fitting time grow with the number of parameters. The second issue is the number of data points used for the fitting. To be meaningful, it should be at least equal to the number of parameters. On the other hand, it should be as small as possible to limit the time needed for the decoding and for determining the model parameters.

To take the real-time constraint under consideration, we now compare the three models when the number of data points used for the fitting is limited to 4, 8, and 4 for (2), (3), and (4) respectively. Figure 1 shows the resulting modeling of the operational MSE-rate function of the SPIHT coder. Here the Weibull model was $y = 1422.99 - 1424.64e^{-0.0053r^{-0.9}}$.

Figure 2 complements Figure 1 by showing the difference in MSE between the models and the true MSE-rate function. The rms error was 125.22, 89.74, and 24.32 for (2), (3), and (4), respectively.

The figures show that under the real-time constraint, the

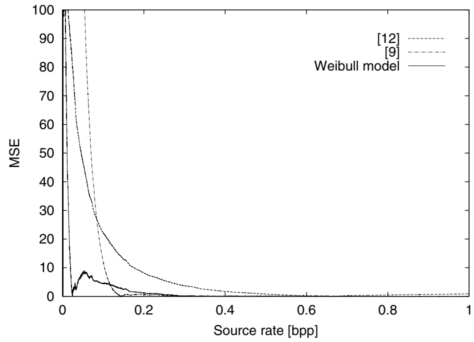

Fig. 2. Difference in MSE between the parametric models and the true MSE-rate function of the SPIHT coder for the 512 × 512 Lenna image.

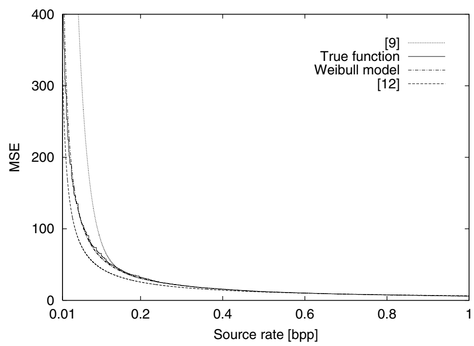

Fig. 3. Comparison between the Weibull model, the model of [9], and the model of [12] with the true MSE-rate function of the JPEG2000 coder for the 512 × 512 Lenna image.

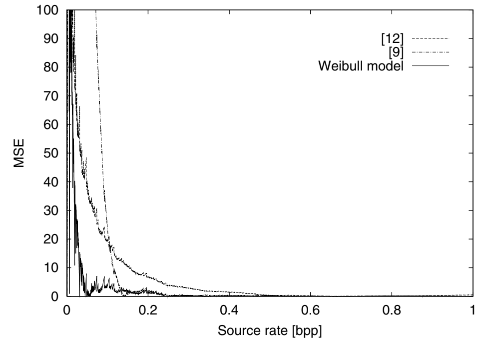

Fig. 4. Difference in MSE between the parametric models and the true MSE-rate function of the JPEG2000 coder for the 512 × 512 Lenna image.

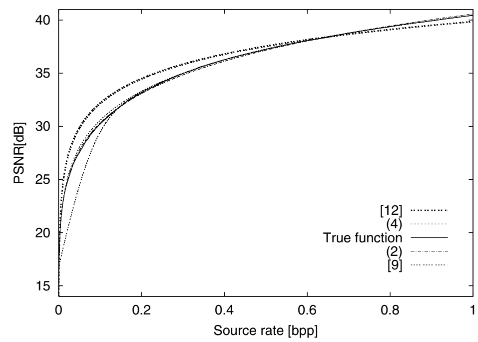

Fig. 5. Comparison between the true PSNR-rate curve of the SPIHT bitstream of the Lenna image, the modeling of this curve with the Weibull model (4), and its modeling with (2). The curves denoted by [9] and [12] are derived from the modeling of the MSE-rate curve with (2) and (3), respectively.

Weibull model significantly outperformed the models of [12] and [9]. In particular, it was better than that of [12] although it has half as many parameters.

We obtained similar results for JPEG2000 (see Figure 3 and Figure 4). Here the Weibull model was $y = 2550.34 - 2550.89e^{-0.0025r^{-0.99}}$.

No model was previously proposed for the operational PSNR-rate function of an embedded wavelet source coder. For example, model (3) is always convex when the c_ks are positive, thus it cannot provide an appropriate fit for the PSNR-rate curve, which is concave. Using relation (1), one could convert the MSE-rate curves found with (2) and (3) into PSNR-rate curves. However, better results are obtained by fitting the operational PSNR-rate points to the models. Figures 5 and 6 show the curves obtained by converting the MSE-rate points and those by fitting the PSNR-rate points to (2) and (4) for the SPIHT and JPEG2000 coders. Here again the Weibull model yielded the best approximation. The models given by (4) were $y = 120.99 - 120.25e^{-0.4r^{0.15}}$ and $y = 105.11 - 117.41e^{-0.6r^{0.12}}$ for SPIHT and JPEG2000, respectively.

Figure 7 compares model (2) and the Weibull model (4) to the true PSNR-rate function of the 3D SPIHT bitstream corresponding to the first 16 frames of the QCIF YUV foreman video sequence. The PSNR was computed for the luminance component and averaged over the 16 decoded frames. The frame rate was 30 frames per second.

Finally we studied the quality of the fitting for various values of the maximum rate R. Our experimental results showed that in contrast to the other models, the Weibull model was not penalized by decreasing the maximum rate R to values as low as 0.125 bpp. This is an advantage because the decoding is faster when the maximum rate is lower.

IV. Experimental Results

In this section, we provide numerical results which show the suitability of the Weibull model to unequal error protection of image and video codes in a binary symmetric channel and unequal loss protection in a packet erasure channel. The state-of-the-art protection algorithms of [17], [3], [18] were used for the study. All simulations were run on a PC with a Linux operating system having an AMD Athlon (TM) XP 1600 1400 MHz processor with a main memory of 1 Gbyte. The programs were written in C and compiled with the -O3 optimization option.

For a given set of channel code rates and a target transmission rate, we determined the highest possible source rate R for an unequal error protection solution. Then we computed the model parameters by using equidistant rates in the range $[0.001, R]$ (see the previous section).

We first give results for unequal error protection over a binary symmetric channel. We used the local search algorithm of [17] to minimize the expected MSE. The source coders were SPIHT and JPEG2000.

The time needed to encode the Lenna image at $R = 1$ bpp was 0.11 s for the SPIHT coder and 0.09 s for JPEG2000. This source rate was the highest one used in our experiments.

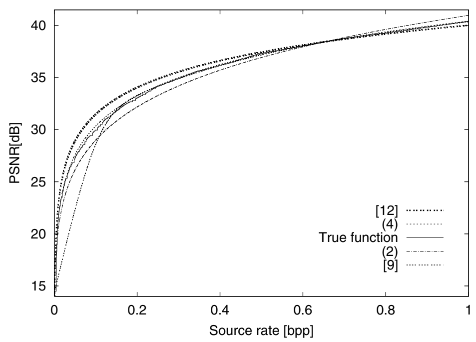

Fig. 6. Comparison between the true PSNR-rate curve of the JPEG2000 bitstream of the Lenna image, the modeling of this curve with the Weibull model (4), and its modeling with (2). The curves denoted by [9] and [12] are derived from the modeling of the MSE-rate curve with (2) and (3), respectively.

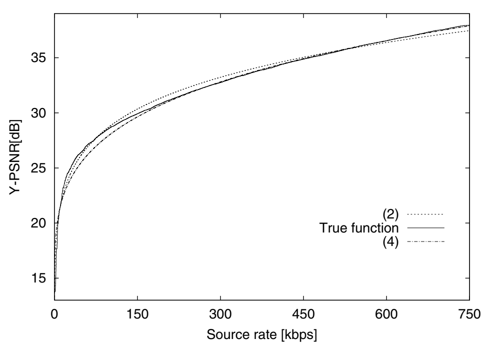

Fig. 7. Modeling of the 3D SPIHT PSNR-rate curve with the Weibull model (4) and model (2). The rate is given in kbits per second (kbps).

For the SPIHT coder (resp. JPEG2000), the time required to compute the MSE-rate points and the model parameters was 0.27 s (resp. 0.14 s) for the Weibull model (four data points, four parameters) and 0.51 s (resp. 0.28 s) for the model of [12] (eight data points, eight parameters).

The overhead that specifies a model consisted of 16 bytes (four single-precision floating point numbers) for the Weibull model and 32 bytes for the model of [12]. If the true distortion-rate curve is computed or if it is estimated in the wavelet domain during the encoding, the encoder needs to send an overhead of $N\lceil\log_2 m\rceil$ bits, where m is the number of channel code rates and N is the number of channel packets. Since $m << N$, and the channel code rates in a solution are nondecreasing [17], one may use run-length encoding (RLE), which requires $m\lceil\log_2 N\rceil + (m-1)\lceil\log_2 m\rceil$ bits in the worst case.

The channel coder was a concatenation of a 32-bit CRC coder and a rate-compatible punctured turbo coder. The turbo coder consisted of two identical recursive systematic convolutional encoders with memory length 4 and generators $(31, 27)$ (octal). The mother code was $20/60 = 1/3$, and the puncturing rate was 20, yielding 41 possible channel code rates. The length of a packet was equal to $L = 2048$ bits, consisting of a variable number of source bits, 32 CRC bits, 4 bits to set the turbo encoder into a state of all zeroes, and protection bits. We used iterative maximum a posteriori decoding, which was stopped if no correct sequence was found after 20 iterations.

Rate	Weibull		[12]		True function
(bpp)	MSE	Time	MSE	Time	MSE
0.25	66.29	< 0.01	66.59	< 0.01	66.32
0.5	34.64	< 0.01	34.63	< 0.01	34.63
0.75	23.20	< 0.01	23.27	0.01	23.26
1.0	17.33	< 0.01	17.33	0.01	17.33
1.25	13.95	0.01	13.95	0.03	13.95
1.5	11.63	0.02	11.63	0.05	11.65

TABLE I

CPU TIME IN SECONDS AND EXPECTED MSE AT VARIOUS TRANSMISSION RATES FOR THE LOCAL SEARCH ALGORITHM OF [17]. RESULTS ARE GIVEN FOR THE SPIHT BITSTREAM OF THE 512×512 LENNA IMAGE. THE BER OF THE BSC IS 0.1.

Rate	Weibull		[12]		True function
(bpp)	MSE	Time	MSE	Time	MSE
0.25	70.42	< 0.01	71.04	< 0.01	71.87
0.5	36.07	< 0.01	36.15	< 0.01	36.96
0.75	23.56	< 0.01	23.46	0.01	23.77
1.0	17.57	< 0.01	17.60	0.02	17.81
1.25	14.12	0.01	14.11	0.03	14.08
1.5	11.72	0.02	11.72	0.05	11.78

TABLE II

CPU TIME IN SECONDS AND EXPECTED MSE AT VARIOUS TRANSMISSION RATES FOR THE LOCAL SEARCH ALGORITHM OF [17]. RESULTS ARE GIVEN FOR THE JPEG2000 BITSTREAM OF THE 512×512 LENNA IMAGE. THE BER OF THE BSC IS 0.1.

Table I and Table II give for SPIHT and JPEG2000 the CPU time and the expected MSE at various transmission rates when the unequal error protection solutions were determined with the Weibull model and the model of [12]. Note that the expected MSE is shown for the true MSE-rate function. The tables also provide the expected MSE when the solution was computed with the true MSE-rate curve.

The performance of the solution found with the Weibull model was similar to the one obtained with the model of [12]. However, the Weibull model allowed a faster computation of the solution. This was due to two reasons. First, (3) is more complex than (4). Second, the local search algorithm applied to (4) needed fewer iterations to converge. The results also show that our model can be used for real-time applications. For JPEG2000, for example, even by adding the 0.23 s needed for the encoding and the modeling of the MSE-rate curve, the Weibull model allows a joint source-channel coding in less than 0.25 s at all transmission rates.

On the other hand, the Weibull model provided almost the same or a lower MSE than the true MSE-rate curve. The gain in performance is due to the fact that the local search algorithm works best when the distortion-rate curve is convex. This condition is fulfilled by models (2), (3), and (4) but is only an assumption for a true distortion-rate curve.

We now consider unequal loss protection. We suppose that N packets of L bytes each are sent over a packet erasure channel. We assume an exponential packet loss model with a mean loss rate of 20 %. We used the unequal loss protection algorithms of [3] and [18] to maximize the expected PSNR. We compare the solutions obtained with the best parametric models, the Weibull model and the model of (2), to those computed with the true PSNR-rate function. Here if the true distortion-rate curve is computed or if it is estimated during the encoding, the encoder needs to send an overhead of $N\lceil\log_2 L\rceil$ bits, which is not negligible. For example, the overhead is 2500 bits for $N = 250$ and $L = 1000$.

Table III and Table IV show the expected PSNR in dB and the time in seconds for the SPIHT bitstream of the Lenna image. The algorithm of [3] computes the vertices of the convex-hull of the PSNR-rate points in a preprocessing step. Since both the Weibull model and model (2) are concave for the PSNR-rate data points, this step is not necessary when the parametric model is used.

Here also using the parametric models instead of the true PSNR-rate function did not cause a significant loss in expected PSNR. Moreover, the time complexity was acceptable for real-time applications. The CPU time of the two models was almost the same. The Weibull model yielded slightly better PSNR results. Table V and Table VI show the results for JPEG2000.

	Weibull		(2)		True function
N	PSNR	Time	PSNR	Time	PSNR
50	31.10	< 0.01	31.10	< 0.01	31.11
100	34.05	< 0.01	34.05	< 0.01	34.06
150	35.77	0.01	35.77	0.01	35.79
200	37.04	0.02	37.04	0.02	37.04
250	38.03	0.03	38.02	0.03	38.02

TABLE III

CPU TIME IN SECONDS AND EXPECTED PSNR IN dB FOR THE ALGORITHM OF [3]. THE RESULTS ARE FOR THE SPIHT BITSTREAM OF THE 512×512 LENNA IMAGE, N PACKETS OF $L = 200$ BYTES EACH, AND AN ERASURE CHANNEL WITH PACKET MEAN LOSS RATE 0.2.

	Weibull		(2)		True function
N	PSNR	Time	PSNR	Time	PSNR
50	31.11	0.02	31.11	0.02	31.13
100	34.06	0.04	34.05	0.04	34.06
150	35.78	0.07	35.78	0.06	35.78
200	37.02	0.09	37.02	0.08	37.01
250	38.03	0.11	38.03	0.11	38.04

TABLE IV

CPU TIME IN SECONDS AND EXPECTED PSNR IN dB FOR THE ALGORITHM OF [18]. THE RESULTS ARE FOR THE SPIHT BITSTREAM OF THE 512×512 LENNA IMAGE, N PACKETS OF $L = 200$ BYTES EACH, AND AN ERASURE CHANNEL WITH PACKET MEAN LOSS RATE 0.2.

Finally, Table VII shows that the Weibull model is also successful for source-channel coding of video. Here 0.31 s were spent for the encoding and 0.8 s were needed to model the PSNR-rate function with the Weibull model.

V. CONCLUSION

We studied optimal unequal error protection of embedded wavelet image and video bitstreams using parametric distortion models of the source coders. We showed that the operational MSE-rate and PSNR-rate functions of the SPIHT, JPEG2000, and 3D SPIHT coders are well approximated by a Weibull model, which outperforms previously proposed models under a real-time constraint. Experimental results showed that the Weibull model is suitable to unequal error protection in binary symmetric channels and unequal loss protection in packet erasure channels.

The main contribution of the paper was to show that parametric distortion-rate models allow real-time unequal error protection and yield PSNR (or MSE) performance comparable to and sometimes better than the one obtained with the true operational distortion-rate curves.

The parametric modeling approach is not limited to the source-channel coding systems considered in this paper; they can also be used with all systems that exploit the distortion-rate function of the source coder, including the powerful product code systems of [6], [7], which were designed for fading channels.

	Weibull		(2)		True function
N	PSNR	Time	PSNR	Time	PSNR
50	30.83	< 0.01	30.81	< 0.01	30.91
100	33.89	< 0.01	33.86	< 0.01	33.92
150	35.71	0.01	35.67	0.01	35.74
200	36.95	0.02	36.90	0.02	36.98
250	37.86	0.03	37.85	0.03	37.92

TABLE V

CPU TIME IN SECONDS AND EXPECTED PSNR IN dB FOR THE ALGORITHM OF [3]. RESULTS ARE GIVEN FOR THE JPEG2000 BITSTREAM OF THE 512×512 LENNA IMAGE, N PACKETS OF $L = 200$ BYTES EACH, AND AN ERASURE CHANNEL WITH PACKET MEAN LOSS RATE 0.2.

	Weibull		(2)		True function
N	PSNR	Time	PSNR	Time	PSNR
50	30.84	0.02	30.83	0.02	30.93
100	33.90	0.05	33.88	0.05	33.92
150	35.72	0.07	35.68	0.07	35.75
200	36.92	0.09	36.91	0.09	36.96
250	37.82	0.11	37.83	0.11	37.89

TABLE VI

CPU TIME IN SECONDS AND EXPECTED PSNR IN dB FOR THE ALGORITHM OF [18]. RESULTS ARE FOR THE JPEG2000 BITSTREAM OF THE 512×512 LENNA IMAGE, N PACKETS OF $L = 200$ BYTES EACH, AND AN ERASURE CHANNEL WITH PACKET MEAN LOSS RATE 0.2.

	Weibull		(2)		True function
N	Y-PSNR	Time	Y-PSNR	Time	Y-PSNR
50	28.96	< 0.01	28.97	< 0.01	29.03
100	31.57	0.01	31.57	0.01	31.58
150	33.48	0.02	33.49	0.02	33.49
200	34.99	0.02	34.99	0.02	34.99
250	36.33	0.03	36.33	0.03	36.34

TABLE VII

CPU TIME IN SECONDS AND EXPECTED Y-PSNR IN dB FOR THE ALGORITHM OF [3]. Y-PSNR DENOTES THE PSNR OF THE LUMINANCE COMPONENT. RESULTS ARE GIVEN FOR THE 3D SPIHT BITSTREAM OF THE FIRST 16 FRAMES OF THE FOREMAN SEQUENCE, N PACKETS OF $L = 200$ BYTES EACH, AND AN ERASURE CHANNEL WITH A PACKET MEAN LOSS RATE OF 0.05.

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