MAP DECODING OF GRAY-LEVEL IMAGES OVER BINARY CHANNELS WITH MEMORY*

Fady Alajaji[†] *Philippe Burlina*[‡] *and Rama Chellappa*[‡]

[†] Department of Mathematics and Statistics, Queen's University, Kingston, ON K7L 3N6, Canada.
[‡] Center for Automation Research, University of Maryland, College Park, MD 20742, USA.

ABSTRACT

A joint source-channel coding technique is proposed for transmitting grey-level images over a binary channel with additive Markov noise. In this scheme, inherent or residual (after source coding) image redundancy is exploited at the receiver in an appropriately designed MAP detector. Two methods are presented. The first method relies on MAP decoding of uncompressed bit-plane encoded images. The second method deals with compressed images (DCT coded and quantized) and uses unequal error protection along with the MAP detection procedure. Experimental results demonstrate that particularly during bad channel conditions, significant performance improvements can be achieved.

1. INTRODUCTION

We address the problem of the reliable communication of images over bursty channels. Traditional approaches to coding images for transmission over a noisy channel use the source-channel coding separation principle resulting in what is commonly known as a tandem source-channel coding system. The optimality of this design principle in cases where no constraints exist on coding/decoding complexity and delay follows from Shannon's work. An alternate approach consists of jointly designing the source and channel codes (joint source-channel coding). This technique has recently received increased attention [2, 3, 5, 6], and has been shown to outperform tandem schemes when delay and complexity are constrained. With the exception of [3, 5], most of the work on joint source-channel coding of images has dealt with the memoryless channel, disregarding the fact that real-world communication channels – e.g., mobile radio or satellite channels – often have memory.

In this work, we investigate the problem of the *maximum a posteriori* (MAP) detection of images transmitted over a binary Markov channel. The MAP detector fully exploits the statistical image characteristics in order to efficiently combat channel noise. It also exploits the larger capacity of the channel with memory as opposed to the interleaved (memoryless) channel. In the first method the inherent image redundancy is exploited: uncompressed images are bit-plane encoded, then directly sent over the channel and MAP detected. In the second scheme the residual redundancy of compressed images is exploited via unequal error protection (UEP) and MAP decoding.

*The work of F. Alajaji was supported in part by the Natural Sciences and Engineering Research Council (NSERC) of Canada under Grant OGP0183645.

2. MAP CHANNEL DECODING

A. Channel Model

We consider a binary channel with memory described by: $Y_i = X_i \oplus Z_i$, for $i = 1, 2, \ldots$ where X_i, Z_i and Y_i represent, respectively, the input, noise and output of the channel. The input and noise sequences are independent from each other. The noise process $\{Z_i\}$ is assumed to be the stationary ergodic Markov process described in [1], with channel bit error rate (BER) denoted by ϵ and correlation parameter denoted by $\delta \geq 0$ (the noise correlation coefficient is given by $\frac{\delta}{1+\delta}$). When $\delta = 0$, the channel reduces to the memoryless binary symmetric channel (BSC) [1]. The channel capacity is monotonically increasing with δ [1].

B. Method 1: Uncompressed Images

The first method describes joint source-channel coding for bit-plane encoded gray level images. In bit plane coding each plane is traditionally compressed using binary image coding techniques [4]. This method is very sensitive to channel errors and typically yields low compression ratios leaving little room for protection against channel noise.

Consider instead directly sending the uncompressed bit-planes modeled as Markov sources over the channel with memory. We use a MAP detection scheme taking into account the source and the channel statistics. This MAP detector is implemented using a modified version of the Viterbi algorithm. The overall algorithm is summarized as follows: The bit-plane image explored in a lexicographic fashion is modeled as a first order Markov process. The line redundancy due to memory ρ_M and redundancy due to non-uniformity in the distribution ρ_D are compared [2]. When $\rho_M << \rho_D$ we transmit the image line over the channel and decode via the MAP algorithm using the line statistics. If $\rho_M >> \rho_D$, the source behaves like a binary symmetric Markov source. When a binary symmetric Markov source is directly sent over a binary Markov channel, a mismatch occurs between the source and channel as the correlation parameter δ increases [2, 3]. One way to remove this mismatch is to use a simple rate-one convolutional encoder which transforms the redundancy in the symmetric Markov source from the form of memory into redundancy in the form of non-uniform distribution [2]. The output of the encoder – modeled as a non-uniform iid process – is then sent over the Markov channel. At the receiver, we use the sequence MAP detector followed by a rate-one convolutional decoder.

C. Method 2: Compressed Images

The first method relies on the intrinsic redundancy of the source to help combat channel noise. In the second method the source is compressed. Since source coding schemes are not ideal, they always leave some residual redundancy in their output bitstream that can similarly be exploited at the receiver.

The source compression technique used is as follows. The image is subdivided in 8 by 8 blocks, and for each of these blocks the discrete cosine transform (DCT) is computed. These are quantized according to the JPEG standard and then encoded via a folded binary code (FBC). Two MAP decoding schemes are proposed:

(a). *MAP-UNC:* Here, no channel coding is performed. For each block, the FBC bitstream is modeled as an iid non-uniform source, sent over the Markov channel and decoded via a MAP detector. In this case, the channel memory and the residual redundancy due to the non-uniform distribution of the FBC data are utilized by the MAP detector to combat channel noise.

(b). *MAP-UEP:* In DCT coding, most of the signal information is concentrated in the lower spatial frequencies. The DC coefficient (the coefficient with zero frequency) is the most important DCT coefficient since it measures the average value of each block. In this scheme, we use UEP by providing additional protection to all of the image DC coefficients: they are channel encoded via a rate 1/2 convolutional encoder (with memory 2). The convolutionally coded DC bitstream is modeled as an iid source, sent over the interleaved Markov channel[1] and MAP decoded. As for the AC coefficients, they are processed without channel coding as in the MAP-UNC scheme.

D. Simulation Results

Experimental results for Method 1 are shown in Figure 1 for two gray-level images: Lena (512x512) and Headscan (256x256). The resulting PSNR plots for the MAP-decoded images show significant improvements over the received images. For $\delta = 10$ and $\epsilon = 0.1$, gains in excess of 6 dB are achieved.

Results for Method 2 are shown in Table 1 and Figure 2 for the images Lena and Baboon (256x256). The source coding rate used for all images is 1.19 bpp. In Table 1 and Figure 2, UNC denotes the uncoded system and ML-UEP-IL represents a traditional tandem source-channel coding scheme with the same UEP technique as MAP-UEP and using maximum likelihood (ML) decoding over the interleaved Markov channel (with $\delta = 0$). For the convolutionally coded systems, the overall coding rate is 1.3 bpp. We can clearly observe from the results that the MAP-UEP scheme offers the best overall performance particularly when the channel is very noisy (high ϵ) and strongly correlated (high δ); it achieves PSNR coding gains of up to 7 dB over the uncoded system and up to 2.5 dB over the tandem scheme.

[1]This can be achieved by interleaving the DC bitstream among the data of the AC coefficients. Interleaving is performed for the DC coefficients since the convolutional code introduces memory in the bitstream; hence, a bursty channel noise behavior can cause an error propagation in the decoder.

δ	System	$\epsilon = 0$	$\epsilon = 0.005$	$\epsilon = 0.01$	$\epsilon = 0.05$	$\epsilon = 0.1$
0	UNC	31.75	24.74	22.06	15.50	12.76
0	MAP-UNC	31.75	24.72	22.14	15.68	13.32
0	ML-UEP-IL	31.75	28.50	26.59	19.83	14.19
0	MAP-UEP	31.75	28.37	26.58	19.94	15.32
10	UNC	31.75	24.00	21.60	14.98	12.03
10	MAP-UNC	31.75	24.39	22.43	16.83	14.49
10	ML-UEP-IL	31.75	28.50	26.59	19.83	14.19
10	MAP-UEP	31.75	29.20	27.70	21.55	15.95
20	UNC	31.75	24.10	21.42	15.38	12.43
20	MAP-UNC	31.75	25.66	23.95	17.69	15.38
20	ML-UEP-IL	31.75	28.50	26.59	19.83	14.19
20	MAP-UEP	31.75	29.93	28.78	22.63	16.33

Table 1: Average PSNR (in dB) of decoded Lena over Markov channel with BER ϵ and correlation parameter δ. Results averaged over five experiments.

3. CONCLUSION

In this paper, we investigate the problem of reliably transmitting grey-level images over binary bursty channels. Two joint source-channel coding schemes that exploit the image statistical characteristics as well as the channel memory via an appropriately designed MAP detector are described and implemented. Experimental results indicate that substantial objective (up to 6-7 dB of PSNR coding gains) as well as subjective performance improvements can be achieved over uncoded systems and tandem source-channel coding systems.

Future work will address the use of soft decision information for the MAP channel decoding of JPEG and MPEG signals over bursty fading channels.

4. REFERENCES

[1] F. Alajaji and T. Fuja. A communication channel modeled on contagion. *IEEE Trans. Inform. Theory*, 40(6):2035–2041, November 1994.

[2] F. Alajaji, N. Phamdo, N. Farvardin, and T. Fuja. Detection of binary sources over discrete channels with additive markov noise. *IEEE Trans. Inform. Theory*, 42(1):230–239, Jan. 1996.

[3] P. Burlina, F. Alajaji, and R. Chellappa. Transmission of two-tone images over noisy channels with memory. In *Proc. Int. Symp. Inform. Theory*, Vancouver, 1995.

[4] A. K. Jain. *Fundamentals of Digital Image Processing*. Prentice Hall Inc., NJ, 1989.

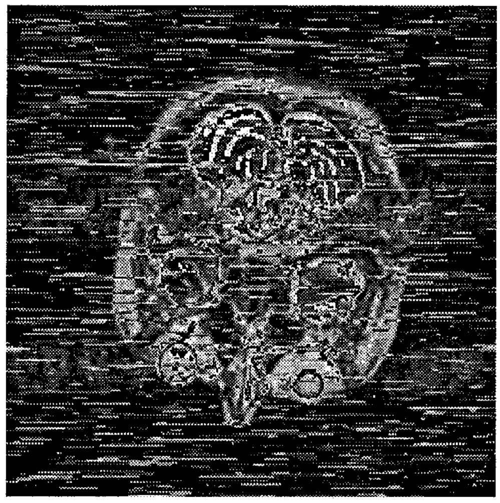
[5] B.S. Srinivas, E.A. Riskin, R. Ladner, and M. Azizoglu. Progressive image transmission on a channel with memory. In *Proc. Allerton Conf. Commun., Control & Computing*, 1995.

[6] W. Xu, J. Hagenauer, and J. Hollmann. Joint source-channel decoding using the residual redundancy in compressed images. In *Proc. Int. Conf. Commun.*, 1996.

(a) Lena: Original.

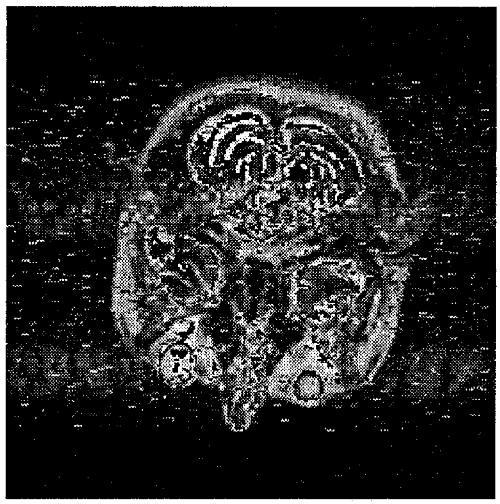
(b) Headscan: Original.

(c) Lena: received Uncoded; $PSNR = 14.45$ dB.



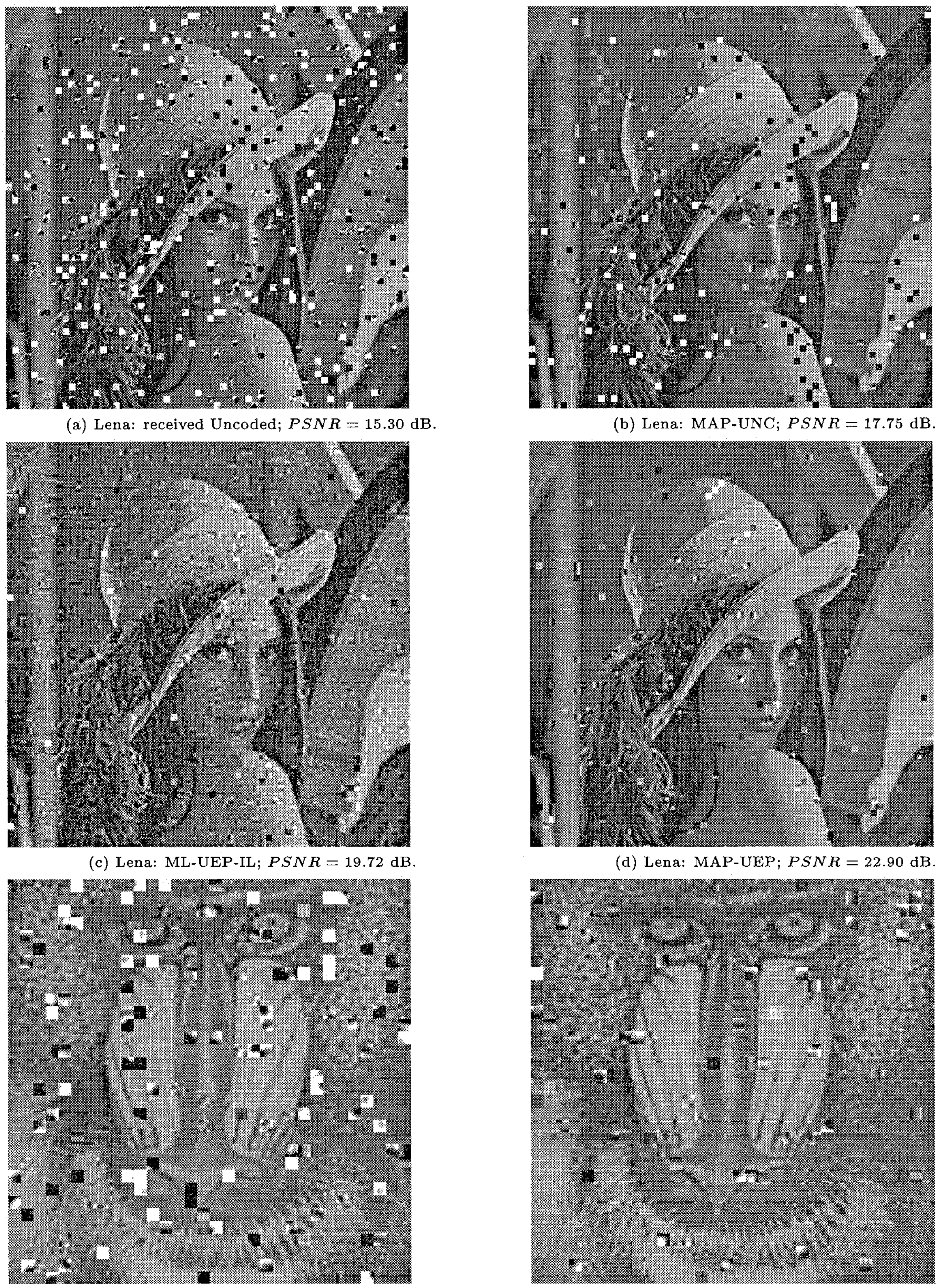
(d) Headscan: received Uncoded; $PSNR = 14.25$ dB.

(e) Decoded Lena: $PSNR = 19.53$ dB.



(f) Decoded Headscan: $PSNR = 20.25$ dB.

Figure 1: Transmission of grey Lena and Headscan using Method 1; $\epsilon = 0.1$, $\delta = 10$.



(a) Lena: received Uncoded; $PSNR = 15.30$ dB.

(b) Lena: MAP-UNC; $PSNR = 17.75$ dB.

(c) Lena: ML-UEP-IL; $PSNR = 19.72$ dB.

(d) Lena: MAP-UEP; $PSNR = 22.90$ dB.

(e) Baboon: received Uncoded; $PSNR = 14.86$ dB.

(f) Baboon: MAP-UEP; $PSNR = 18.76$ dB.

Figure 2: Transmission of grey Lena and Baboon using Method 2; $\epsilon = 0.05$; $\delta = 20$.