JOINT SOURCE-CHANNEL CODING USING STRUCTURED OVERSAMPLED FILTERS BANKS APPLIED TO IMAGE TRANSMISSION

Abraham Gabay *, *Oli vier Rioul*

ENST
46 rue Barrault
75634 Paris Cedex, France.
(gabay@tsi.enst.fr, rioul@com.enst.fr

Pierre Duhamel

CNRS/LSS
Plateau de Moulon
F-91192 Gif sur Yvette Cedex, FRANCE.
pierre.duhamel@lss.supelec.fr

ABSTRACT

This paper proposes a new joint source and channel coder based on the BCH codes on the reals, in which the signal protection (analogous to a signal interpolation) is performed *before* compression. This allows a better tradeoff in high accuracy compression, since part of the distortion introduced by the compression can be corrected by the "channel decoder". Furthermore, we propose as an optimal code allocation procedure, which allows to obtain a good robustness, too, when the errors introduced by the channel increase. the resulting rate/distortion curves outperform those obtained by a separate system on the whole range of operation.

Although presented in the context of image transmission through a Binary Symetric Channel, the resulting codes may be employed on a wide range of transmission schemes with significant performance benefits.

1. INTRODUCTION

It is known that classical source coders may produce large amplitude errors if the resulting bit stream is sent over noisy channels. Consider the simple example of a scalar quantizer, with the resulting bit stream sent over a Binary Symmetric channel (BSC): While quantization produces errors of small amplitude in the reconstructed data, channel errors have the effect of producing impulse noise of larger amplitude, if some channel error hits a MSB.

A classical approach to solve this problem is to use *channel coding*: one inserts redundancy at the output of the source encoder to make it easier for the receiver to detect and/or correct the erroneously received data. Thus, protecting against errors results in an increase in bandwith (see figure 1).

An end-to-end communication system is composed of a system encoder, which maps the source symbols into channel inputs, and a system decoder, which maps the channel outputs into noisy reproductions of the original source symbols. The system encoder can be further broken down into a source encoder, which maps the source symbols into an intermediate alphabet, typically a set of binary strings, and a channel encoder, which maps the binary strings into coded bits or waveforms for transmission over the channel. Similarly,th e system decoder can be broken down into a channel decoder and a source decoder corresponding to the respective channel and source encoders. Any system encoder-decoder pair can be represented in this manner, although the breakdown is not unique. Shannon's classical separa-

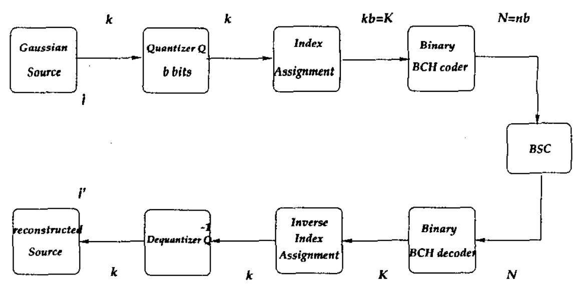

Fig. 1. Principle of an end-to-end separated communication scheme

tion result states that we can optimize the end-to-end system performance by separately optimizing the source encoder-decoder pair and the channel encoder-decoder pair. However, this result holds only in the limit of infinite source code dimension and infinite channel code block length. Shannon theory does not provide a design algorithm for good channel codes with finite block length. In addition, Shannon theory does not address the design of good source codes when the probability of channel error is nonzero, which is unavoidable for finite-length channel codes. Thus, for practical systems, in which the delay or complexity is constrained, a joint source and channel code design may reduce distortion. The benefits one can expect from a joint procedure are

*This work has been supported by the French space agency (CNES) and Alcatel Space Industries Toulouse.

larger when the constraints increase.

Our first contribution consists in expressing a workable channel model for the joint source and channel situation we are investigating.

2. CHANNEL MODEL

Let us consider again the scalar quantization of a gaussian source s to be transmitted over a BSC with a resolution of b bits. This quantization may be non uniform. The quantization process chooses among the dictionnary $(d_0, d_1, d_2, ..., d_{2^b-1})$ the nearest neighbor centroid, and its index represents the source s to be encoded.

This process generally introduces relatively small error amplitudes. However, the presence of a memoryless BSC of parameter p introduces additional distortion, which has to be considered in a joint system design. The total error added to the source by the quantization and the channel is clearly modeled by

$$\hat{s}'_j = d_j + n_j + e_j \qquad j$$

where n_j is the quantization noise (assumed white) and e_j is the impulse "error" due to the BSC channel. The impulse error probability that $e_j \neq 0$ is $p = 1 - (1 - \epsilon)^b$ where b is the number of quantized bits per sample and ϵ is the BSC bit error probability.T ypically when $e_j \neq 0$, e_j takes larger values than n_j.

It appears that background noise added to impulse noise exactly describes how each sample is affected, by the quantization process and the channel errors [3]. It turns out that, in many situations, this channel can be modeled with a good accuracy by a sum of Gaussian and Bernouilli-Gaussian noise, the parameters of which depend on the precise situation. (For example, a very good fit can be obtained when transmitting MDP8 modulation on an AWGN channel, which is not obvious at first glance . . .)

3. STRUCTURED OVERSAMPLED FILTER BANKS

3.1. Oversampling procedure

The knowledge of the channel errors can be used to introduce a structured redundancy in order to detect and correct impulses. This method [4] is similar in spirit to the approach proposed by Sayood and Borkenhagen [1] which combines both channel and source statistics in the design of the source coder. However, it differs in that the protection is done in such a way as to be independant of the statistics of the source : the initial transformation of classical source encoder (iterated filterbank) is kept untouched, for turning the initial image into a set of (almost) decorrelated sources with stable pdf, and a carefully designed redundancy is added to

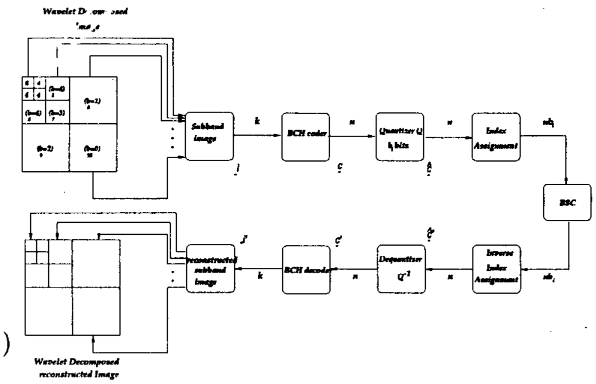

Fig. 2. Principle of the structured oversampled filter banks scheme

the information words prior to quantization in order to provide protection. This redundancy is added using the formalism of a real-valued BCH code. and exploits the knowledge of the channel characteristics and quantization to restore the received data.

Hence, a first interpretation is that we have deliberately introduced redundancy in the source (and in a structured manner) in order to do joint decoding. This is the link with [1].

However, when looking at the system from the initial image to the outpout of the BCH enbcoder,it can be viewed exactly as a strutured oversampled filter banks properly designed for the channel model (see figure 2).

3.2. Link to other methods

The oversampling procedure can also be seen as a special case of the expansion-quantization-reconstruction scenario depicted in [2]. In our case the encoding equation can be written as

$$\underbrace{\underline{c}}_{n\times 1} = \underbrace{\underline{\underline{W_n}}^{-1}}_{n\times n} \underbrace{\underline{\underline{P}}}_{n\times k} \underbrace{\underline{\underline{W_k}}}_{k\times k} \times \underbrace{\underline{i}}_{k\times 1}$$

where $\underline{\underline{W_l}}$ is the length-l DFT matrix, $\underline{\underline{P}}$ is the $n - k$ zero-padding matrix.

The codeword components c_j, $j = 0, 1, \ldots, n-1$ are then quantized as in [2].

It can also be described as a BCH coding, in the infinite field of the real numbers [7, 6, 4]. Figure 3 summarizes the link between these procedures. It appears that the structured oversampling procedure, can be viewed as a BCH encoding procedure setting to zero 2 t consecutives frequencies. The problem is how to use the redundancy present in the quantized codewords to be able to correct the errors introduced

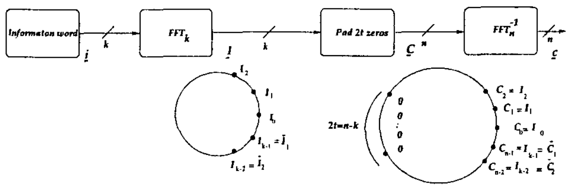

Fig. 3. Oversampling from the information word to the expanded BCH encoded signal

by the channel. This is solved in the next section using the language of BCH codes.

3.3. Description of the decoding algorithm

The decoding problem can be rephrased as follows. Given a noisy codeword $\hat{\underline{c}'}$ input to the decoder,estim ate the transmitted codeword $\underline{c}'$ in order to finally reconstruct the initial source word $\underline{s}'$.

We use the redundancy introduced by oversampling to simultaneously localize and correct impulse noise samples *and* reduce quantization noise. The decoding algorithm is based on the fact that $n - k$ consecutives DFT components of the codeword $\underline{c}$ vanish. After quantization and transmission, the corresponding components of $\hat{\underline{c}'}$ will no longer take zero values even when no channel errors have been introduced. These components are first computed in the spectral domain by the decoder. They constitute the so-called *syndrome* [5] which is used as a "signature" of the impulse noise to be removed in the presence of the background noise. In this syndrome, simple mathematics show that the impulse errors show up as complex sinusoids (the frequencies of which characterize the error location), polluted by background noise (the Fourier transform of the quantization noise)

The decoding algorithm is then composed of three steps: (1) evaluate the number of impulses considered as "errors," (2) find the error locations and (3) find and correct the error values to recover $\underline{c}'$. Blahut [5]d escribes several efficient algorithms for doing this, but unfortunately these are very sensitive to quantization noise. Therefore, we have followed the approach outlined in [7], which is a modified version of the classical Peterson-Gorenstein-Zierler algorithm adapted to the real number case:

(1) The number of "error impulses" is first determined as the rank of a suitable "syndrome matrix," taking the statistical contribution of the quantization noise into account.

(2) Then, we solve a Yule-Walker system to compute the error-locator polynomial, whose roots give the location of the impulses.

(3) Finally, from the estimated locations we solve an overdetermined Van der Monde system in the least squares sense to estimate the impulse amplitudes.

At each step of the algorithm, we are able to detect possible problems with the decoder, by a procedure which will be described in a forthcoming paper. If this happens, we begin a truncated enumeration of the possible error locations among the most likely ones, until correction. If this correction does not happen, and would we insist on correcting errors there would be a significant increase in distortion, since the decoder would introduce additional errors. Therefore, in this case, the algorithm stops and the noisy input data $\hat{\underline{c}'}$ is directly output as $\underline{c}'$.

As a final step, the corrected word is "projected back to the code": the $n - k$ spectral components are removed in order to recover the source word $\underline{s}'$ by inverting the encoding process. Notice that when no "impulse" is detected at the reception, this last step will always reduce the quantization distortion. This cannot occur in a classical "separated" scheme[4].

Note that, in image compression, we use a product code : along the rows and the columns, the decoding being iterated between both dimensions.

4. SIMULATION RESULTS

Simulations were done using a 1000×1000 satellite image , and the $(9 - 7)$ Daubechies bi-othogonal filter, and compared to the actual separate encoder (denoted as "binary BCH in the curves).

Figure 4 gives the end-to-end PSNR in the reconstructed image relative to the initial satellite image, as a function of the BSC bit error probability ϵ for both oversampled and separated schemes.

The numerical values were $R_s = 2$ bits/pixels ,th e 1-D code was $(n = 51, k = 31, t = 10)$,the code used for the product code was the $(n' = 19, k' = 15, t' = 2)$ and the binary BCH code was $(N = 63, K = 39, t = 4)$, giving a global rate around 3.25 transmitted bits per pixel in each case (satellite imaging requires very high quality : these are actual numbers ...). The best oversampled scheme is clearly more robust to channel noise than the TSC scheme for the whole range of ϵ values. For example, we obtain a 1.4dB improvement in PSNR over the classical TSC scheme for very small BSC crossover probability.

5. SHOHAM-GERSHO OPTIMISATION

For a given crossover probability and a global rate, the presented method of real BCH coding prior to quantization can be optimized by carefully choosing a set of quantizers, and a set of oversampled product codes for each subband image.

This can be done by using the bit allocation algorithm decsribed in [9] to allocate in an optimal manner the GLOBAL

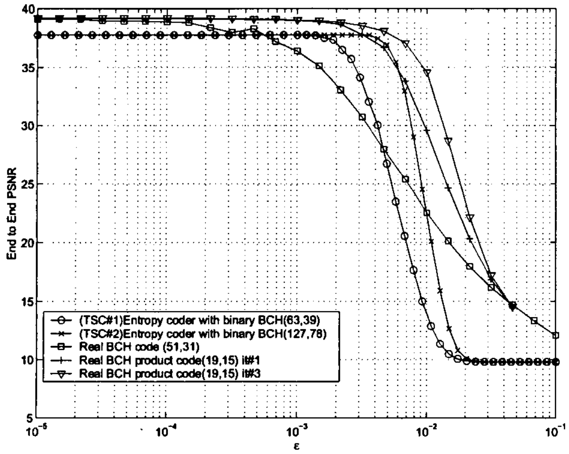

Fig. 4. End-to-end PSNR comparison of oversampling and Binary BCH (TSC) coding schemes.

bit-rate to each subband (i.e. choosing altogether the quantization and protection).

Figure 5 shows the performance obtained by such optimisation, compared to the traditionnal TSC scheme. The oversampling scheme outperforms the TSC scheme: since "channel coding" occurs before quantization, high amplitude errors issued from quantization, are also considered as impulse noise and can be removed. For a rate of 3.2 bits per pixel, a 3.7 dB improvement over the TSC scheme is observed.

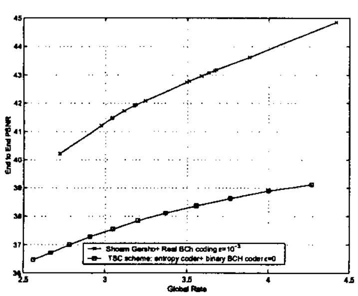

Fig. 5. PSNR comparaison of the real BCH coding approach with the TSC scheme

Furthermore, the approach gives us the hierachical protection and the resolution to achieve, for each subband. This also results in a better performance for any channel error probability.

6. CONCLUSION

The presented method of oversampling prior to quantization and its decoding algorithm is able to reduce distortion introduced not only by the transmission channel errors but also by the quantizer since the joint approach allow a global modelisation of the errors.

The decoding algorithm is therefore suitable to increase the end-to-end PSNR since it deals simultaneously with the quantization noise and impulse channel noise.

Compared to classical TSC scheme, our structured oversampling approach is more robust to channel noise for a large range of crossover propability, thus allowing efficient *joint* source and channel decoding.

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