Iterative Joint Source-Channel Decoding with source statistics estimation: Application to image transmission

Haifa Belhadj, Sonia Zaibi and Ammar Bouallegue
bel_haifa@yahoo.fr, sonia.zaibi@enit.rnu.tn, ammar.bouallegue@enit.rnu.tn

Abstract. This paper deals with iterative joint source channel decoding and its application to image transmission. First, the problem of transmitting a correlated gaussian source over an AWGN channel is considered. The joint decoding is implemented by the Baum Welch algorithm estimating the source statistics. Iterations between the MAP channel decoder and the source decoder are made to improve the global decoder performance. This decoding scheme is then applied to an image transmission system, based on a wavelet decomposition of the source image followed by a DPCM coding of the lowest frequency subband and a SPIHT coding of high frequency subbands. Simulation results show that a significant performance gain is obtained with iterative joint source channel decoding, compared to a classical decoding, in case of a correlated gaussian source and also in case of image transmission.

Keywords: Joint Source-Channel Decoding, Iterative Decoding, Baum-Welch Algorithm, DWT, DPCM, SPIHT.

1 Introduction

In traditional communications systems, source and channel coding are performed separately. However, the separation between source and channel coding has turned out to be not justified in practical systems due to limited coding/decoding delay and system complexity. On these circumstances, one can improve performance by considering the source and channel design jointly. Research on this area goes back to the work of Fine [1] and continuous to the present [2].

On the other hand, Turbo-codes [3], with their iterative decoding techniques, achieve very good performance, which are close to the theoretical limit of Shannon.

In this paper, we consider the problem of transmitting a correlated source over an AWGN (Additive White Gaussian Noise) channel. This source is protected by a convolutional code. We use the turbo codes principle to release an iterative joint source channel decoding algorithm with estimation of source statistics. This scheme is applied to an image transmission system. In the first section, we briefly remind the Baum-Welch algorithm principle, applied to joint source-channel decoding. The turbo decoding principle is used in the second section, to release an Iterative Joint Source Channel Decoding (IJSCD) algorithm. Performances of iterative decoding for a correlated gaussian source transmission are presented in section 3. In the forth section, the IJSCD is applied to an image transmission system, based on a wavelet decomposition of the source image followed by a DPCM (Differential Pulse Code Modulation) coding of the lowest frequency subband and a SPIHT (Set Partitioning in Hierarchical Trees) coding for high frequency subbands. Finally, simulation results for the lowest frequency subband and the entire image, are respectively given. Section 5 draws conclusions and suggests future work.

2 Joint source-channel decoding and estimation of correlated source parameters

We consider the problem of encoding and transmitting a source signal vector $\boldsymbol{I}=\{i_0,i_1,\ldots,i_t,\ldots,i_{T-1}\}$ over a noisy channel. We still want to know the sequence of transmitted source indexes i_t but they are not directly observable because of the possible corruption by the channel. Instead, we have the received indexes, $\boldsymbol{O}=\{o_0,o_1,\ldots,o_t,\ldots,o_{T-1}\}$, which are the observations related to the input probabilistically. This situation can be directly interpreted as a discrete Hidden Markov Model (HMM). A discrete HMM can be defined by two parameters and three probability matrices. The parameters are K the number of states, and T the source sequence length [4]. To determine, at each time, the most likelihood symbol, we use the BCJR (Bahl Cocke Jelinek and Raviv) algorithm originally proposed in [5] and based on the forward-backward algorithms. The BCJR allows to calculate the *a posteriori* probability denoted $\gamma_t(i)$:

$$\gamma_t(i) = P[I_t = i | O, \lambda] \ . \tag{1}$$

To calculate $\gamma_t(i)$, we need to determine two variables: α_t(i) and β_t(i). The BCJR algorithm combines the forward induction with the backward one to compute the probabilities $\gamma_t(i)$. For more details refer to [5]. The methods above allow to determine the most likelihood *a posteriori* symbol, where $\gamma_t(i)$ is maximum, with consideration of a hidden Markov source whose parameters are known. A more powerful approach would allow the receiver to use the noise-corrupted observations available in the decoder to estimate the parameters characterizing the hidden Markov source. We will estimate source statistics by the Baum-Welch algorithm called also EM [6][7].

Estimation of source parameters at the receiver

We try to estimate the source transition matrix *A*. Its elements $a_{i,j}$ are the source transition probabilities:

$$a_{i,j} = P[I_t = j | I_{t-1} = i], \quad 0 \le i, j \le K-1 \ . \tag{2}$$

To do that, we introduce a new parameter $\Psi_t(i;j)$ representing the probability that source state is *i* at the time *t* and *j* at time $t+1$:

$$\psi_t(i,j) = P[I_t = i, I_{t+1} = j | O, \lambda] = \frac{a_{i,j} P[O_{t+1} = o_{t+1} | I_{t+1} = j] \alpha_t(i) \beta_{t+1}(j)}{\sum_{i=0}^{K-1} \alpha_t(i) \beta_t(i)} \ . \tag{3}$$

The re-estimation formula is then given by:

$$a_{i,j} = \frac{\sum_{t=0}^{T-2} \psi_t(i,j)}{\sum_{t=0}^{T-2} \gamma_t(i)} \ . \tag{4}$$

After having re-estimated the parameter *A* of the initial hidden Markov model, the algorithm will repeat iteratively the re-estimation with the new model (we calculate another time the α and β values).This process can be repeated iteratively until no further improvement in the model results. The transition source matrix *A* is initialised as follows: $a_{i,j}^{(0)} = P[I_t = j]$. After calculating the *a posteriori* probabilities, we determine at each time *t*, the value $\hat{\imath}_t$ maximising $\gamma_t(i)$. $\hat{\imath}_t$ is the most likelihood symbol value at the time *t* which will be decoded.

3 Iterative joint source-channel decoding

3.1 System model

We consider the system model shown in figure1. The correlated source produces a sequence of *T* continuous-valued, gaussian distributed symbols, with a variance equal to 1 and a correlation factor equal to 0.9. Each symbol of the sequence is quantized by a scalar quantizer, that produces a sequence of indices ***I***= $(i_0, \ldots, i_t, \ldots i_{T-1})$. According to a fixed length bit mapping, each index i_t is assigned a unique binary sequence $\boldsymbol{B}_t = (b_{t,1}, \ldots b_{t,L})$, which generates a bit sequence

$\boldsymbol{B} = (B_0,......,B_t,.....B_{T-1})$ of length $K=T*L$ bits, where L is the binary code word length. This bit sequence is bitwise interleaved with an interleave denoted $\boldsymbol{\pi}$, before being coded by a recursive systematic convolutional encoder and transmitted over an AWGN channel using BPSK modulation. The received sequence is denoted $\boldsymbol{Y}=(y_0,...,y_t......,y_{T-1})$; $y_t = (y_{t,1},....,y_{t,l},....,y_{t,L})$. It constitutes the iterative decoder input.

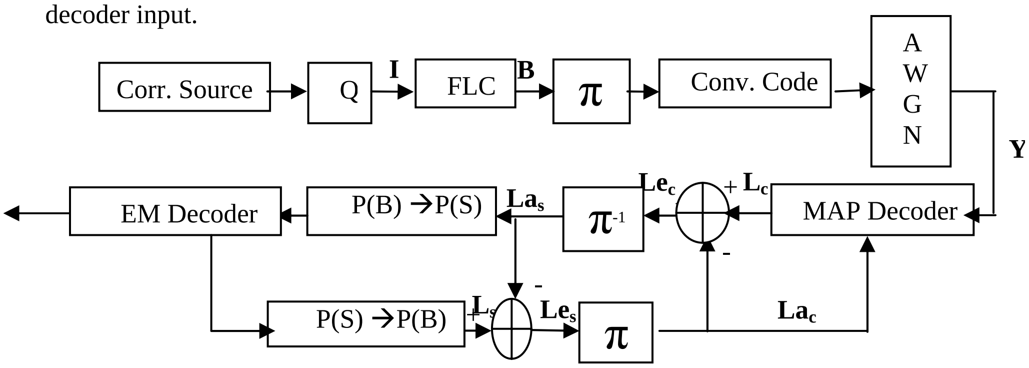

Fig.1. System model with IJSCD *(Q: Scalar Quantizer, FLC: Fixed Length Bit Mapper, π: Interleaver)*

Both source and channel decoders are Soft In/Soft Out (SISO). The MAP algorithm is used as a channel decoder, while the Baum-Welch (EM) algorithm is used as a source decoder estimating source statistics. The Iterative Joint Source Channel Decoding (IJSCD) method will now be described.

3.2 Iterative Joint Source Channel Decoding (IJSCD) method

The iterative decoding scheme is related to turbo decoding. It consists of a data exchange between two or more channel decoders which are SISO decoders. The source and channel decoders receive and send their messages in terms of Log-Likelihood Ratio (LLR). Let's remind that we have an information exchange between the source decoder, operating with symbol data, and the channel decoder working with bit data. So we need conversion blocks P(S)→P(B) and P(B)→P(S), which allow to calculate bit probabilities from symbol ones and back again. The channel decoder allows us to determine an *a priori* information La_s for the source decoder. However, this information is a bit information and the Baum-Welch algorithm needs a symbol one. The conversion bloc P(B)→P(S) is used to calculate symbol probabilities from bit ones. Formally, if we write the probabilities for each bit input to the P(B) →P(S) block as $P_A(b_{t,l} = c)$, where $c \in \{0,1\}$, then symbol probabilities are approximated by the product of the corresponding bit probabilities:

$$P(I_t = i) = \prod_{l=1}^{L} P_A(b_{t,l} = map_l(i)) \ . \tag{5}$$

where $map_l(i)$ is the bit of position l in the bit word mapping the symbol i. The probability P_A is determined from the *a priori* information La_s:

$$La_s(b_{t,l}) = \ln\left(\frac{P_A(b_{t,l}=1)}{P_A(b_{t,l}=0)}\right). \quad (6)$$

At the output of the source decoder, we need to know the bit probabilities to calculate the extrinsic information rescued at the channel decoder. The Baum-Welch algorithm used for the source decoding provides the *a posteriori* symbol probabilities. Therefore, we need to apply the P(S)→P(B) conversion. The bit probabilities are derived from the symbol ones as follows:

$$P(b_{t,l}=c) = \sum_{i/map_l(i)=c} P(I_t=i) \; . \quad (7)$$

Then, the source decoder output is given by:

$$L_s(b_{t,l}) = \ln\left(\frac{P(b_{t,l}=1)}{P(b_{t,l}=0)}\right) . \quad (8)$$

We subtract the *a priori* information values La_s from this information to get the extrinsic values Le_s, rescued, after interleaving, to the channel decoder as an *a priori* information La_c . This decoding procedure is repeated iteratively. We pull up when performances stop to improve.

4 Simulation results (Case of a correlated Gaussian source)

To evaluate the proposed system (figure1) performances, we plotted the Bit Error Ratio (BER) evolution, as a function of the signal to noise ratio Eb/N0. The results achieved are compared to a transmission chain using a classical decoding scheme (without iterative joint source channel decoding), considered as a reference chain. This chain uses in fact, the Viterbi algorithm as a channel decoder. We have considered the transmission of a sequence of 400 symbols, issued from a one-order Markov Gaussian source, with a variance equal to 1 and a correlation factor equal to 0.9. Each symbol value is quantized by a one step uniform scalar quantizer. The quantized indexes belong to a source alphabet of size 7. The fixed length bit mapper (FLC) associates to each quantized index a 3-bit binary code word. We have used a recursive systematic convolutional code [8] with generator polynomials (37, 21) and rate ½. The used interleaver is a random one of size 20*60. Simulation results are represented on figure 2:

-IJSCD: iter4 refers to a transmission chain with iterative joint source-channel decoding, with source perfect knowledge, at the forth iteration.

-IJSCD+EM:iter i refers to a transmission chain with iterative joint source-channel decoding, with source statistics estimation, at the iteration i.

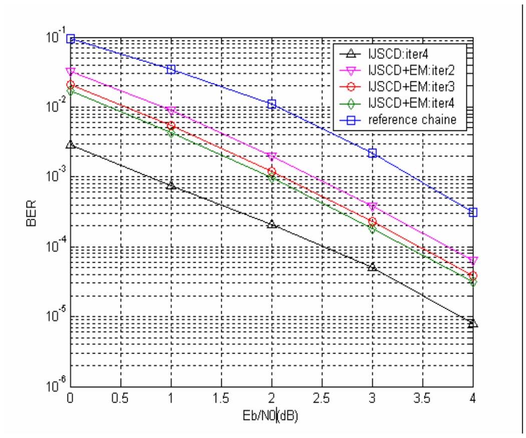

Fig.2. BER as a function of Eb/N0 for transmission systems without and with (IJSCD) (with and without estimation)

We notice that for a BER of 3.10^{-4}, a gain of 1.5dB in Eb/N0, is achieved by the iterative decoding system with source statistics estimation (DICSC+EM) comparing to the reference chain. The gain is more than 2dB, for the iterative decoding with perfect knowledge of source statistics. For a signal to noise ratio of 4dB, the BER is near 10^{-5} for the transmission system with iterative joint source-channel decoding (perfect knowledge statistics), and only about 3.10^{-4} for the reference chain.
So we can conclude that the proposed transmission system, bring a strong gain in performances comparing to a classical system based on a separated source and channel decoding.

5 Application to image transmission

The majority of efficient image compression algorithms use a transformation, applied to the original signal, a quantization and an entropy coding. According to the choice of the transformation, the quantization and the entropy coding, many compression schemes have been proposed. One of the most used transformations for image coding is the Discrete Wavelet Transformation (DWT) [9].

5.1 DWT and SPIHT principle

The discrete wavelet transformation is derived from the multiresolution analysis, developed by Stephane Mallat and Yves Meyer [10]. The aim of this theory is to decompose a signal into different resolutions. The lowest frequency subband contains the most important information of the image. The high frequency subbands constitute the image details.

We use in our work, one of the most powerful wavelet-based image compression method: the SPIHT (Set Partitioning in Hierarchical Trees) [11]. It is an image compression algorithm exploiting the inherent similarities across subbands in a wavelet decomposition of an image. The SPIHT compression principle is based on the use of the zero-trees, in the wavelet subbands in order to reduce redundancies between them. Spatial orientation trees are created; they contain all the wavelet coefficients at the same spatial locations in the finer resolution subbands. Fig.3 shows an example of spatial orientation trees in a typical three level subband decomposition. The wavelet coefficients are encoded according to their nature: *root* of a possible zero-tree or *insignificant set*, *insignificant* pixel and *significant* pixel. The significance map is efficiently encoded by exploiting the inter-subband correlations and the bitplane approach is retained to encode the refinement bits. The SPIHT algorithm is mainly based on the management of three lists (List of Insignificant Sets, List of Insignificant Pixels and List of Significant Pixels). An iterative process successively scans and encodes the coefficients of each spatiotemporal tree [11].

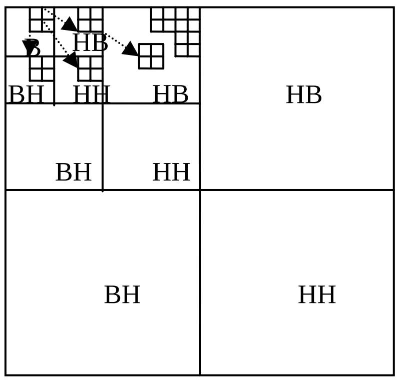

Fig.3. Inter-subband dependencies used by the SPIHT algorithm.

5.2 Proposed image transmission system

The block diagram of the proposed image transmission system is given in figure 4. In this system, we use an image compression algorithm based on the DWT. The Lowest Frequency Subband LFS is coded separately from the Highest Frequency Subbands HFS. This allows unequal error protection to be easily applied. Also, if only a few levels decomposition are used, the decoded LFS would give a reasonable approximation of the entire image. The wavelet coefficients in the LFS are scalar quantized and then DPCM encoded. The latter is done by first finding a predicted value, for each coefficient, the prediction of a sample is merely the value of the previous sample. The predicted value is then subtracted from the coefficient to give residual coefficient, which is typically encoded. The HFS are encoded by the SPIHT algorithm. The SPIHT coder provides good compression performance, but it is quite sensitive to bit errors. A convolutional code is then used for channel coding.

The DPCM encoder leads to correlation among the transmitted indexes that can be considered as a first order Markov process. The idea is to apply the iterative joint source-channel decoding method, described in section 3, to data issued from the DPCM encoding of the LFS, in order to improve the image decoding. In the system that we propose, the wavelet coefficients of the LFS are scalar quantized and then DPCM encoded. Each obtained symbol is mapped into a binary code word. The resulting binary data are encoded using a recursive systematic convolutional code, and then transmitted over an AWGN channel. The iterative joint source-channel decoding method is applied at the receiver to decode the LFS data. The wavelet coefficients of the HFS subbands are coded by the SPIHT algorithm followed by a convolutional code. They are transmitted over the AWGN channel, then, they are decoded using the Viterbi algorithm followed by the SPIHT decoder. All subbands are regrouped. We finally apply a wavelet inverse transformation to restore the whole image.

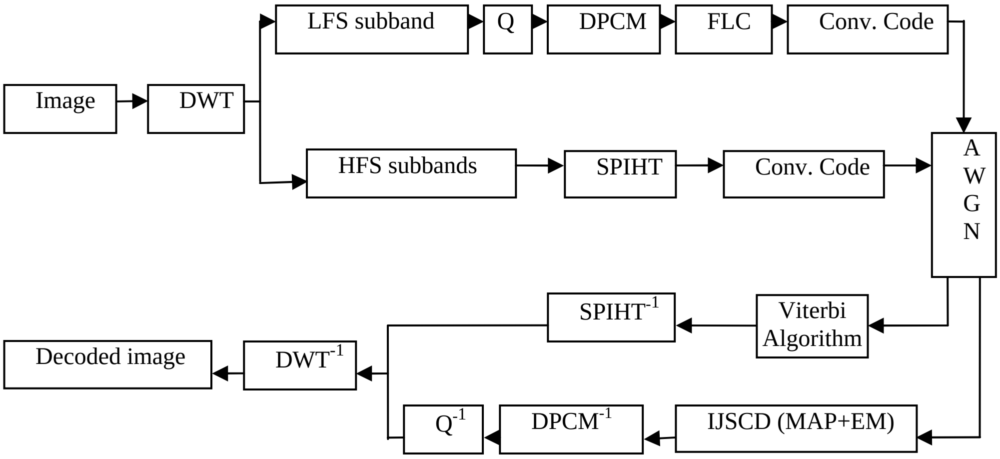

Fig.4. Proposed image transmission system

5.3 Experimental results

In all our simulations, the Lena image of size 512*512 pixels (8 bpp), is used as a test image. A three level wavelet decomposition is applied to the image, using the 9-7 filters. So the number of wavelet coefficients in the LFS is equal to 4096. These coefficients are quantized by a uniform scalar quantizer and then DPCM encoded. Each obtained symbol is represented by a 7-bit binary code word. So we have a binary frame of 28672 bits representing the LFS data. This frame is shared into 32 packets (each packet has a length of 896 bits). These packets are then encoded by a recursive systematic convolutional code with generator polynomials (37, 21) and rate ½ . They are transmitted over an AWGN channel. The IJSCD method, described in section 2 is applied at the receiver to decode the LFS data. The number of iterations is fixed to 3. The wavelet coefficients of the HFS subbands are coded by the SPIHT algorithm followed by a convolutional code with generator polynomials (37, 21) and rate ½ . The rate at the output of the source coder is fixed to 1 bpp.

The results are averaged over 500 channel realizations. In order to visualize the contribution of iterative joint decoding, we compared performance in terms of PSNR of the lowest frequency subband (PSNR-LFS), for the two systems without and with IJSCD decoding and source statistics estimation. Let's recall that our system applies IJSCD only to the LFS data, and that our reference system uses a separate source and channel decoding for both LFS and HFS data. The figure 5 represents the variation of the PSNR of the lowest frequency subband (PSNR-LFS) according to the signal to noise ratio E_b/N_0.

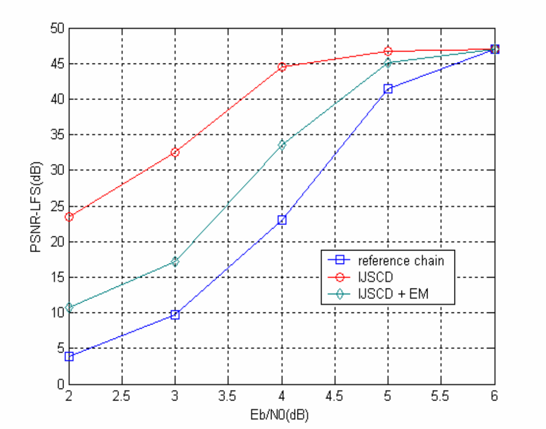

Fig.5. PSNR of lowest frequency subband

We can see that a significant gain in the PSNR of the LFS is obtained by using IJSCD. Indeed for a signal to noise ratio E_b/N_0=4dB, we have a gain of about 8dB.
The figure 6 represents the variation of the PSNR of the entire image according to the signal to noise ratio E_b/N_0, for the image transmission systems without and with IJSCD and source statistics estimation.

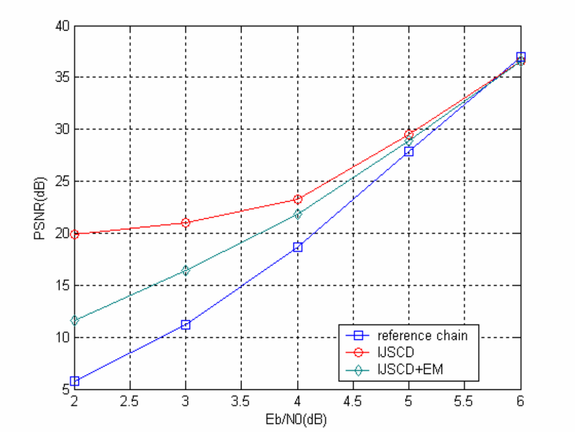

Fig.6. PSNR of the entire image

We can note that a significant gain in PSNR is achieved by iterative joint source channel decoding, comparing to classical decoding. This gain is about 1 dB for E_b/N_0=5dB.

6. Conclusions

An efficient joint source channel decoding method, implemented by an iterative algorithm, and applied to an image transmission system is stated in this paper. The principle of this iterative algorithm is inspired from the turbo codes one; it uses the Baum Welch algorithm to estimate the source parameters at the receiver. A convolutional code is used for channel coding. Simulation show that, in case of a correlated gaussian source transmission, iterative joint source-channel decoding leads to a significant performance gain, in comparison with classical decoding. This iterative decoding scheme is applied to an image transmission system based on a wavelet transformation and a DPCM coding of the LFS and a SPIHT coding of the HFS. Channel coding is performed with a convolutional code. The simulation results indicate that the use of iterative joint decoding for the LFS data, can improve the error resilience of the image transmission system. The primary area of future research is improving the source compression, by using a variable length code instead of the fixed length one. We can also use turbo codes to improve the error protection.

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