Error Resilient Turbo Compression of Source Codec Parameters Using Inner Irregular Codes

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Abstract— In this paper, we present a novel near-lossless compression scheme for scalar quantized source codec parameters. The scheme is comparable to a Turbo source coding approach and can inherently incorporate protection against transmission errors. We show that using the concept of EXIT charts and inner irregular convolutional codes of rate > 1, a linear programming optimization problem can be formulated resulting in the minimization of the transmitted number of bits given a certain channel quality. The solution of this problem leads to an irregular inner code offering the best possible compression. The advantage of this method in comparison to a previous proposal is the easy adaptability to varying source conditions.

I. INTRODUCTION

With the discovery of Turbo codes, channel coding close to the Shannon limit has become possible with moderate computational complexity. In the recent years, the Turbo principle of exchanging *extrinsic* information between separate channel decoders has also been adapted to other receiver components. To exploit the residual redundancy in source codec parameters such as scale factors or predictor coefficients for speech, audio, and video signals in a Turbo process, *iterative source-channel decoding* (ISCD) has been proposed in [1], [2] as a means to further improve the quality of *soft decision source decoding* (SDSD) [3]. This residual redundancy occurs due to nonideal source encoding resulting from, e.g., delay or complexity constraints.

In [4] and [5], it has been shown that Turbo codes can also be used as source encoders. Conventional entropy source encoders such as Huffman codes or arithmetic codes are very sensitive to transmission errors while the Turbo source coding approach automatically incorporates error protection and can adapt on the fly to changing channel conditions by increasing or decreasing the amount of artificial redundancy introduced by the channel code.

In [6], we have presented a novel concept for the nearlossless compression of scalar quantized source codec parameters based on a joint source-channel coding approach with ISCD at the receiver. The utilized inner channel code was a fixed code of rate $r \ge 1$ and the outer code was an irregular redundant index assignment, as proposed in [7]. The irregular index assignment has been optimized according to the concept of irregular codes [8], allowing for a simple optimization This work was financed in part by the European Union under Grant FP6-2002-IST-C 020023-2 *FlexCode* and in part by the **IUMIC** Research Centre, RWTH Aachen University using EXIT charts [9], a convenient tool for the convergence analysis of iteratively decoded concatenated codes. In order to realize source compression, the optimization guideline of [8] and [7] has been modified in [6], leading to a linear program. The limitations of the approach in [6] is that whenever the properties of the source change, new EXIT characteristics of the source with different index assignments have to be computed before performing a new optimization.

Here, we propose an approach which does not optimize the outer component of the serially concatenated transmitter but the inner component, i.e., the channel code. The approach is based on irregular inner codes, as used, e.g., in [10], with a different optimization goal however. These codes have the advantage that their EXIT characteristic can easily be approximated using the characteristic of a mother code [11]. The other advantage of this approach is that the optimization can more easily cope with varying source properties. Thus, we present a system based on inner irregular codes that realizes an efficient, flexible compression scheme which can easily adapt to varying source conditions.

II. SYSTEM MODEL

In Fig. 1 the baseband model of the considered ISCD system is depicted. At time instant t a source encoder generates a frame $\mathbf{u}_t = (u_{1,t}, \dots, u_{K_S,t})$ of K_S unquantized source codec parameters u_{κ} with $\kappa \in \{1, \ldots, K_S\}$ denoting the position in the frame. Each value u_{κ} is individually mapped to a quantizer reproduction level \bar{u}_{κ} , with $\bar{u}_{\kappa} \in \mathbb{U} = \{\bar{u}^{(1)}, \dots, \bar{u}^{(Q)}\}$. The set U denotes the quantizer codebook with a total number of $|\mathbb{U}| = Q$ codebook entries. Without loss of generality, we restrict Q to take only values which are powers of 2, i.e., $Q = 2^M$, with $M \in \mathbb{N}$. A unique bit pattern $\mathbf{b}_{\kappa} \in \mathbb{B} = {\mathbf{b}^{(1)}, \dots, \mathbf{b}^{(Q)}}$ of M^{\star} bits (i.e., $\mathbb{B} \subseteq \mathbb{F}_2^{M^{\star}}, \mathbb{F} =$ $\{0, 1\}$), is assigned to each quantizer level \bar{u}_{κ} according to the index assignment $\Gamma_{\kappa}(\bar{u}^{(i)}) = \mathbf{b}^{(i)}, i = 1, \dots, Q$. The index assignment (which is also often denoted as bit mapping in the literature) thus assigns a bit pattern $\mathbf{b}^{(i)}$ to the quantization index i. For notational convenience we omit the time index t in the following if the meaning of the equation is non-ambiguous.

The single bits of a bit pattern \mathbf{b}_{κ} are indicated by $b_{\kappa}(m)$, $m \in \{1, \ldots, M^{\star}\}$. We define in this work $M^{\star} \doteq M + 1$. As $M^{\star} = M + 1 > \log_2 Q = M$, the index assignment Γ_{κ} is called *redundant index assignment* as it introduces redundancy: here one more bit than actually necessary is



spent to represent a quantizer reproduction level. It is known that redundant index assignments can lead to significant improvements in the context of ISCD [12]. The index assignment can be considered to be the composite function $\Gamma_{\kappa}(\bar{u}) = \Gamma_{\kappa}^{R}(\Gamma^{NR}(\bar{u}))$. First, the function Γ^{NR} performs a nonredundant mapping of the Q quantizer reproduction levels to patterns consisting of M bits. Second, the function Γ_{κ}^{R} can be regarded as a (potentially non-linear) block code. In this contribution, the function Γ_{κ}^{R} realizes a single parity check code, i.e., the bit pattern \mathbf{b}_{κ} can be written as

$$\mathbf{b}_{\kappa} = (b_{\kappa}(1), \dots, b_{\kappa}(M), b_{\kappa}(1) \oplus b_{\kappa}(2) \oplus \dots \oplus b_{\kappa}(M)), (1)$$

with $b_{\kappa}(1), \ldots, b_{\kappa}(M)$ being the natural binary representation of the quantizer index *i*. The rate of the (redundant) index assignment is $r^{IA} = \frac{M}{M+1}$. After the index assignment, K_S bit patterns are grouped to a frame of bit patterns $\mathbf{x} = (\mathbf{b}_1, \ldots, \mathbf{b}_{K_S})$ consisting of $N_X \doteq K_S \cdot (M+1)$ bits. The frame \mathbf{x} of bits is rearranged by a bit interleaver π in a deterministic, pseudo-random like manner. The interleaved frame is denoted as \mathbf{x} .

As, according to [13], a necessary condition for a serially concatenated system to be capacity achieving is an inner component with code rate $r^{\text{inner}} \ge 1$, we use an irregular convolutional code of rate $r^{\text{CC}} > 1$ as proposed in [10] for channel encoding of a frame $\check{\mathbf{x}}$. The irregular convolutional encoder is depicted in Fig. 2. The input bit frame $\check{\mathbf{x}}$ is partitioned into N_{CC} different sub-frames $\check{\mathbf{x}}_{\ell}^{[\text{irr]}}$ of length $L_{\ell}^{[\text{irr]}}$, $\ell \in \{1, \ldots, N_{\text{CC}}\}$ which are individually encoded by one of the N_{CC} dedicated convolutional encoders. Note that $\sum_{\ell=1}^{N_{\text{CC}}} L_{\ell}^{[\text{irr]}} = K_S \cdot (M+1)$. Each of these convolutional encoders is a randomly punctured recursive convolutional code of memory J_{ℓ} and of rate r_{ℓ}^{CC} according to [14]. All the convolutional codes are assumed to be zero terminated, i.e., J_{ℓ} tail bits are appended to each $\check{\mathbf{x}}_{\ell}^{[\text{irr]}}$. The length of the encoded frame amounts approximately to

$$L_{\rm CC} \approx \sum_{\ell=1}^{N_{\rm CC}} \left[\frac{L_{\ell}^{\rm [irr]} + J_{\ell}}{r_{\ell}^{\rm CC}} \right] \,. \tag{2}$$

Note that the length can only be approximately given as due to the random puncturing, the exact size depends on the



Fig. 2. Irregular convolutional encoder

state of the random number generator influencing the resulting puncturing pattern. The total rate of the inner irregular encoder thus amounts to $\overline{r}^{\text{inner}} = \frac{N_X}{L_{CC}} = \frac{K_S(M+1)}{L_{CC}}$. Randomly punctured codes have been introduced in [14]

Randomly punctured codes have been introduced in [14] and consist of (in our case) a rate 1/2 recursive systematic convolutional (RSC) code punctured with a random puncturing matrix to a rate of r_{ℓ}^{CC} . Besides their final rate, they are also characterized by the fraction $P_{\text{sys},\ell}$ of punctured systematic bits. Using $P_{\text{sys},\ell}$ and r_{ℓ}^{CC} , the fraction of punctured nonsystematic bits can be computed and the puncturing can be performed using a Bernoulli random number generator. For more details, we refer the reader to [14].

The encoded frame of length $L_{\rm CC}$ is denoted by y. The bits y_k of y are indexed by $k \in \{1, \ldots, L_{\rm CC}\}$. Prior to transmission over the channel, the encoded bits y_k are mapped to bipolar values \ddot{y}_k forming a sequence $\ddot{y} \in \{\pm 1\}^{L_{\rm CC}}$. On the channel, the (modulation) symbols \ddot{y}_k (with symbol energy $E_{\rm s} = 1$) are subject to additive white Gaussian noise (AWGN) with known power spectral density $\sigma_n^2 = N_0/2$.

The received symbols z_k are transformed to *L*-values [15] prior to being evaluated in a Turbo process which exchanges *extrinsic* reliabilities between channel decoder (CD) and soft decision source decoder (SDSD). The irregular channel decoder demultiplexes the received symbols into $N_{\rm CC}$ different sub-streams according to the partitioning performed inside the irregular encoder. Each of these $N_{\rm CC}$ sub-streams is individually decoded using a MAP algorithm [16] and the resulting *L*-values are multiplexed to a single stream. For the equations of the SDSD, we refer to the literature, e.g., [1], [12]. After a given number of iterations, the block entitled *Parameter Estimation* performs a MAP estimation and selects an estimated parameter $\hat{u}_{\kappa,t} \in \mathbb{U}$.

III. NEAR-LOSSLESS SOURCE CODING USING INNER IRREGULAR CODES

It has been shown in, e.g., [4] and [5], that Turbo codes can be efficiently used as source codes, realizing a near-lossless compression scheme. Near-lossless means that a perfect reconstruction cannot be guaranteed but a small amount of errors has to be tolerated. With some slight modifications (see, e.g., [17]) lossless entropy coding schemes can be realized with Turbo codes. Classical entropy coding compression schemes like Huffman or arithmetic codes are able to achieve high compression ratios with moderate computational complexity, however, in the presence of channel noise, severe error propagation and synchronization losses may occur. Soft decision source decoding and iterative source-channel decoding can also be applied to entropy codes [18] at the cost of increased computational complexity. It has been shown in [14] that a system utilizing fixed-length codes can achieve comparable results (in terms of reconstruction quality and symbol error rate) to a system with variable-length codes, with lower computational complexity at the receiver if channel noise is present.

In [6] we have used an ISCD system with redundant index assignments for realizing a near-lossless source coding system. The convolutional code in that case was a rate > 1 code obtained by deterministic puncturing of a rate < 1 mother code. The index assignment was irregular and designed to minimize the number of transmitted bits after channel coding. In this contribution we employ a fixed redundant index assignment and optimize the inner channel code such that the number of transmitted bits is minimized. The minimization is based on an optimization in the EXIT chart domain using the concept of irregular codes [8]. Several component codes of different rates are used to encode parts of the current frame. The overall EXIT characteristic of the code is the weighted superposition of the EXIT characteristic of the different sub-codes. Irregular convolutional codes as inner codes have been successfully employed in the context of iterative source-channel decoding in [10]. However, the optimization goal in [10] was a different one as in the present paper: here we minimize the number of bits that are transmitted over the channel whereas in [10] the squared error between the EXIT functions of source and channel decoder was minimized.

In order to perform source coding, the optimization goal is to find an EXIT characteristic which results in the smallest number of transmitted bits with the constraint that an open decoding tunnel in the EXIT chart exists. We assume that a total number $N_{\rm CC}$ of different convolutional code configurations are available. The code shall be optimized at a design channel quality $\frac{E_s}{N_0}$. The EXIT characteristics $\mathcal{C}_{\ell}^{\text{CC}}$ of the different randomly punctured convolutional codes are recorded at the design $\frac{E_s}{N_0}$. One advantage of randomly punctured convolutional codes is that their EXIT characteristic can be computed from the characteristic of the mother code [11]. It is assumed that \mathcal{C}^{CC}_{ℓ} is composed of P sample points of the EXIT characteristic. The sampled characteristics are placed into a matrix C of dimension $P \times N_{\rm CC}$. Furthermore, the EXIT characteristic C^{SDSD} of the SDSD given the single parity check code redundant index assignment is recorded and P sample points of its inverse $[\mathcal{C}^{\text{SDSD}}]^{-1}$ are stored in the column vector d.

During the optimization of the irregular inner code, we seek for weights w_{ℓ} which determine the amount of bits of \breve{x} that are encoded by the ℓ -th code. This means that $L_{\ell}^{[\text{irr]}} = w_{\ell} N_X$. The goal of the optimization is to minimize the number of bits L_{CC} under the constraint that the data can be recovered at the receiver. This corresponds to a classical compression scheme: we want to transmit the minimum number of bits and reconstruct the original data at the receiver. The number of bits $L_{\rm CC}$ can be expressed as

$$L_{\rm CC} \approx \sum_{\ell=1}^{N_{\rm CC}} \frac{w_\ell N_X + J_\ell}{r_\ell^{\rm CC}} = \sum_{\ell=1}^{N_{\rm CC}} \frac{w_\ell N_X}{r_\ell^{\rm CC}} + \sum_{\ell=1}^{N_{\rm CC}} \frac{J_\ell}{r_\ell^{\rm CC}}$$
$$= N_X \cdot \tilde{\mathbf{r}}^T \mathbf{w} + K \tag{3}$$

with $\tilde{\mathbf{r}} = \left(\frac{1}{r_1^{\text{CC}}}, \dots, \frac{1}{r_{N_{\text{CC}}}^{\text{CC}}}\right)^T$ and the weighting factors $\mathbf{w} = (w_1, \dots, w_{N_{\text{CC}}})^T$. The factor $K = \tilde{\mathbf{r}}^T \mathbf{j}$, with $\mathbf{j} = (J_1, \dots, J_{N_{\text{CC}}})$ is a constant offset factor which is due to the termination of the different sub-codes. Note that for performance and complexity considerations, we do not consider non-terminated and tailbiting codes in this contribution. Minimizing L_{CC} thus leads to the linear program

$$\mathbf{w}_{\text{opt}} = \arg\min\tilde{\mathbf{r}}^T\mathbf{w} \tag{4}$$

subject to the (equality and inequality) constraints

$$\mathbf{C} \cdot \mathbf{w} \succ \mathbf{d} + \mathbf{o} \tag{5}$$

$$0 \le w_{\ell} \le 1 \quad \forall \ell \in \{1, \dots, N_{\rm CC}\}$$
(6)

$$\sum_{\ell=1}^{N_{\rm CC}} w_{\ell} = 1 \,, \tag{7}$$

The solution to this linear programming optimization problem can be easily found using numerical methods (see, e.g., [19]). The constraint (5) states that all elements of the vector Cw have to be element-wise larger than the corresponding elements of d + o (operator " \succ ") and guarantees an open decoding tunnel in the EXIT chart. An open decoding tunnel signifies that the resulting EXIT characteristic of the irregular code C_{irr}^{CC} , obtained by weighting all the utilized N_{CC} convolutional codes with w (P sample points of C_{irr}^{CC} are given by $\mathbf{C} \cdot \mathbf{w}$), has no intersection with the inverse SDSD characteristic stored in d. In (5), the vector o denotes an offset vector which is chosen such that a larger open decoding tunnel is present, leading to better convergence properties at the receiver. In fact, the constraint $\mathbf{Cw} \succ \mathbf{d}$ would only guarantee an infinitely small decoding tunnel which cannot be exploited by a practical system. By an adequately chosen o, the convergence and the decoding complexity (which linearly scales with the number of iterations) can be controlled. However, a penalty in the compression performance has to be tolerated if the decoding tunnel becomes wider, as the optimization tends to select codes with lower rates in order to fulfill the constraints. The constraints (6) and (7) ensure that the w_{ℓ} are valid weighting factors.

In the case of large block lengths, $N_X \cdot \tilde{\mathbf{r}}^T \mathbf{w} \gg K$ and the effect of the termination can be neglected. However, as soon as N_X becomes smaller, the length of the compressed bit stream considerably increases with the number of utilized codes, as the constant additive term $K = \tilde{\mathbf{r}}^T \mathbf{j}$ grows with $N_{\rm CC}$. Therefore, we propose an advanced scheme which further minimizes the number of bits $L_{\rm CC}$ after source compression. Starting with a pool of $N_{\rm CC,tot}$ codes, we try all the combinations of $1 \leq N_{\rm CC} \leq N_{\rm CC,tot}$ and select the subset which results in the

TABLE I Utilized randomly punctured convolutional codes, mother code with generator polynomial $(1, \frac{17}{11})$

ℓ	$r_\ell^{\rm CC}$	$P_{\mathrm{sys},\ell}$	l	$r_\ell^{\rm CC}$	$P_{\mathrm{sys},\ell}$
1	1.25	0.91	7	3.5	0.98
2	1.5	0.93	8	4.0	0.98
3	1.75	0.93	9	5.0	0.99
4	2.0	0.94	10	6.0	0.99
5	2.5	0.94	11	8.0	0.99
6	3.0	0.96	12	10.0	0.99

smallest number of bits $L_{\rm CC}$. For a given $N_{\rm CC}$, we first select one of the $\binom{N_{\rm CC,tot}}{N_{\rm CC}}$ subsets of $N_{\rm CC}$ codes and try to perform the optimization using this limited space of codes. If the linear program (4) can be solved and if the resulting $L_{\rm CC}$ evaluated using (3) is smaller than all previously computed values, we retain this subset of codes. This means that a total number of $\sum_{N_{\rm CC}=1}^{N_{\rm CC,tot}} \binom{N_{\rm CC,tot}}{N_{\rm CC}} = 2^{N_{\rm CC,tot}} - 1$ linear programs have to be solved (full search). This is only practical if the number $N_{\rm CC,tot}$ is relatively small.

IV. EXAMPLES

We demonstrate the concept of near-lossless source coding using irregular index assignments by two simulation examples. For the simulation examples, we assume a simplified model in order to generate reproducible results. A source coder extracts K_S parameters from an arbitrary (audiovisual) signal. The K_S parameters are be modeled as i.i.d. Gaussian processes with zero mean and unit variance. We further assume that the parameters originate from a Markov chain with correlation coefficient $\rho = \frac{\text{Cov}(U_{\kappa,t},U_{\kappa,t-1})}{\text{Var}(U_{\kappa,t}) \text{Var}(U_{\kappa,t-1})} = \text{Cov}(U_{\kappa,t},U_{\kappa,t-1})$. This means that the source encoder removes all correlation within one frame $(Cov(U_{\kappa,t}, U_{\kappa-1,t}) = 0$, so-called intraframe redundancy) but due to the computational complexity limitations and the limited frame length, leaves correlation between consecutive frames \mathbf{u}_{t-1} and \mathbf{u}_t . This source setup can be used for instance to model the behaviour of transform coefficients in transform-based audio codecs. One example of such a codec, where the proposed algorithm has been successfully utilized is the *FlexCode* source coder [20], [21]. Another example where this model can be applied are the gains of speech and audio codecs.

The parameters are quantized using a *constrained entropy* scalar quantizer (CESQ) [22]. In the case of CESQ, the optimum scalar quantizer is a uniform scalar quantizer with step size s_s [23] which is followed by an entropy encoder (like Huffman or arithmetic codes). In our proposal, the system consisting of redundant index assignment, interleaver and irregular inner channel encoder constitutes the entropy encoder.

The parameters of the utilized inner randomly punctured codes according to [14] are summarized in Table I. They are all based on a recursive systematic mother code of rate $\frac{1}{2}$ with octal generator polynomials $(1, \frac{11}{17})$ and $J_{\ell} = 3$, $\forall \ell \in \{1, \ldots, N_{\text{CC,tot}}\}$.

A. Error-free channel: Mere Compression

In the first example, we assume that no channel errors occur, i.e., $\mathbf{n} = \mathbf{0}$ in Fig. 1 (or $E_s/N_0 \rightarrow \infty$, respectively).



Fig. 3. EXIT chart example for irregular inner codes with $\rho=0$ for $E_{\rm s}/N_0\to\infty$

First, we also assume that the correlation of the source is not exploited by the soft decision source decoder. This means that the SDSD assumes a source of K_S i.i.d. uncorrelated Gaussian parameters. As a typical example, the quantizer step size is set to $s_s = 0.5$ and the number of quantization levels is fixed to Q = 16, leading to M = 4 bit. The resulting source entropy is H(U) = 3.0615 bit which is the lower bound for a reliable transmission/storage of the given setup. Using the above codes and the redundant index assignment consisting of a single parity bit described in Sec. II, the optimization guideline presented in Sec. III leads to the following results: the set of $N_{\rm CC} = 3$ codes with $\ell \in \{1; 2; 6\}$ is utilized with weighting factors $w_1 = 0.1223$, $w_2 = 0.6967$, $w_6 = 0.1810$.

Figure 3 depicts the resulting EXIT chart optimization. The characteristics C_{ℓ}^{CC} of the $N_{\text{CC,tot}} = 12$ codes are depicted as gray dashed lines in the figure. The EXIT characteristic C^{SDSD} of the SDSD which only exploits AK0 knowledge (i.e., the Gaussian distribution of the source) is also given in Fig. 3. We denote the SDSD using only the distribution of the signal by AK0-SDSD. The EXIT characteristic of the optimized inner code, given by $\mathcal{C}_{irr}^{CC} = w_1 \mathcal{C}_1^{CC} + w_2 \mathcal{C}_2^{CC} + w_6 \mathcal{C}_6^{CC}$ is also given in Fig. 3: it can be seen that a narrow decoding tunnel is present between C_{irr}^{CC} and C^{SDSD} which allows the reconstruction at the transmitter using a high number of iterations. For $K_S = 256$ and the given exemplary setup, we can achieve a number of bits per parameter $L_{\rm CC}/K_S \approx 3.1349$ bit. Compared to the entropy of the source, the difference amounts to $L_{\rm CC}/K_S$ – H(U) = 0.0734 bit. Our previous approach presented in [6], which optimizes the outer code component (i.e., the redundant index assignment) leads to 3.1527 bit/parameter which is slightly worse.

In the context of CESQ, the entropy encoder compresses the data on a frame-by-frame basis. In speech and audio codecs employed in a real-time conversational scenario a low end-to-end delay is mandatory. Often such codecs operate on frames of 20 ms length. Usually, the entropy code does not exploit eventual dependencies between consecutive frames. For instance, an arithmetic code uses the distribution of the different parameters for determining its probability intervals in the context of CESQ but usually does not make use of any



Fig. 4. EXIT chart example for irregular inner codes with $\rho=0.9$ for $E_{\rm s}/N_0\to\infty$

information from the previous frame. The main advantage of SDSD is that it can easily exploit the inter-frame redundancies at the receiver without increasing the system delay [3]. If the correlation coefficient $\rho > 0$, this *a priori* knowledge of first order (AK1) is exploited within the SDSD (therefore denoted as AK1-SDSD) and leads to a different EXIT characteristic C_{ρ}^{SDSD} . For $\rho = 0.9$ this characteristic is depicted in Fig. 4 together with the characteristics of the $N_{\text{CC,tot}}$ inner codes which remain unchanged compared to Fig. 3.

The optimization using the AK1-SDSD yields codes of higher rates and realizes therefore a better compression. The codes selected by the optimization are the codes with $\ell \in$ $\{2; 5; 7\}$ (N_{CC} = 3). If the total number of bits is evaluated using (3), we get $L_{CC}/K_S = 2.387$ bit < H(U). However, the bound in this case is the conditional entropy $H(U_t|U_{t-1}) =$ 1.9784 bit. Note that the system AK1-SDSD still has a gap of ≈ 0.4 bit to the conditional entropy which is due to the fact that the AK1-SDSD does not fully exploit the Markov property and only utilizes information from the previous frame but not from future frames due to delay constraints. An AK1-SDSD with full forward-backward decoding would even show better performance (compare [6], where the full forward-backward algorithm has been employed and a performance close to the conditional entropy has been obtained). However, in order to have a system comparable with existing approaches in terms of system delay, we did not use the full forward-backward decoder in this contribution. Further note that the transmitter does not require any changes apart from a different code selection. No additional delay is introduced and the only changes are being made at the receiving side by employing a different SDSD algorithm.

B. AWGN Channel: Error-Resilient Compression

A major advantage of the presented approach is its resilience against transmission errors. For instance, if additive Gaussian noise is present on the channel, the characteristics of the inner codes $C_{\ell}^{\rm CC}$ are modified because the amount of information present at the channel output is decreased by the noise. The EXIT chart results for a channel quality $E_{\rm s}/N_0 = 0$ dB are given in Fig. 5. It can be clearly seen that the amount of extrinsic information $\mathcal{I}_{\rm CD}^{\rm [ext]}$ generated by the different sub-



Fig. 5. EXIT chart example for irregular inner codes with $\rho=0.9$ for $E_{\rm s}/N_0=0\,{\rm dB}$

decoders is smaller than in the error-free case. Again, the optimizer selects $N_{\rm CC} = 3$ codes ($\ell \in \{1;3;5\}$) in this setup. The number of bits per parameter, computed using (3), amounts to 3.3270 bit which is only slightly higher than H(U). This means that the given system realizes a joint source-channel coding approach that minimizes the number of transmitted bits at a channel quality of $E_{\rm s}/N_0 = 0$ dB while maintaining decodability.

C. Simulation Example

Figure 6 shows simulation results for the optimization from Fig. 5. The goal was to realize a system that achieves maximum compression at $E_s/N_0 = 0 \, dB$ and also works for better channel qualities. The offset vector o in the constraint (5) was set to $0.005 \cdot \mathbf{1}_{P \times 1}$ leading to a narrow decoding tunnel. Note that in all previous EXIT charts the offset vector has been chosen to o = 0. The simulations were performed for $K_S = 256$ which is a typical value for transforms employed in audio and image codecs and for $K_S = 8192$. The upper part of Fig. 6 depicts the Parameter SNR $(\frac{E\{U^2\}}{E\{(U-\hat{U})^2\}})$ between original and estimated parameters. The system presented in [6] which uses an optimized irregular index assignment and a fixed rate-2 inner convolutional code serves as a reference. Both systems employ 30 ISCD iterations at the receiver and the AK1-SDSD algorithm which only considers the previous frame and no information from future frames. The number of bits per parameter is approximately identical for both systems and amounts to ≈ 3.40 bit for this setup. This value is slightly higher than the value given above due to the non-zero offset vector o.

It can be clearly seen from Fig. 6 that the proposed system outperforms the reference which has been optimized for the same channel quality. This can be explained by the curved EXIT decoding tunnel of the reference system (see Fig. 2 in [6]) compared to the "straight" tunnel in Fig. 5. Due to the limited block length, the iterative decoder has more difficulties to pass the "curved" decoding tunnel than the "straight" tunnel. If the number of parameters per frame is increased to $K_S = 8192$, the waterfall behavior is more pronounced and the performance difference system even slightly outperforms



Fig. 6. Simulation results (parameter SNR and symbol error rate) in the presence of channel noise, 30 decoding iterations

the proposed setup in terms of a lower error-floor. The better waterfall behavior is expected and can be explained by the increased block length. The lower part of Fig. 6 shows the symbol error rate (SER) between the quantized parameters \bar{u}_{κ} and their estimates \hat{u}_{κ} and confirms the results.

V. CONCLUSIONS

In this contribution we have shown that a joint sourcechannel coding approach with irregular inner codes and iterative decoding can be effectively utilized for near-lossless error resilient Turbo source coding. In a source coding setup, the number of transmitted bits shall be minimized. Minimizing the number of bits leads to a linear programming optimization problem. The solution of this optimization is an irregular inner code, which is realized using randomly punctured convolutional codes. The advantage of these codes is that their EXIT characteristics can easily be computed from the characteristic of a common mother code. The other advantage over the system previously presented in [6] is that changes of the source properties can easily be taken into account without recomputing a vast number of EXIT characteristics required for optimizing the irregular index assignment.

The performance of the proposed system has been evaluated based on two simulation examples. In a first example, an error-free channel has been assumed and it has been shown that our system is able to compress the given source with a performance close to the source entropy. Furthermore, we have shown how the inter-frame redundancies of the source can be taken into account to further boost the system performance. In a second simulation example, we have shown the abilities of the system in the presence of channel noise. The simulation results indicate that the optimization goal is reached with a practical system and that the reference system can even be outperformed for small block lengths.

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