ITERATIVE SOURCE-CHANNEL DECODER USING EXTRINSIC INFORMATION FROM SOFTBIT-SOURCE DECODING

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ABSTRACT

In digital mobile communications efficient compression algorithms are needed to encode speech or audio signals. As the determined source parameters are highly sensitive to transmission errors, robust source and channel decoding schemes are required.

This contribution deals with an iterative source-channel decoding approach where a simple channel decoder and a softbit-source decoder are concatenated. We will mainly focus on softbit-source decoding which can be considered as error concealment technique. This technique utilizes residual redundancy remaining after source coding.

In this paper we derive a new formula that shows how the residual redundancy transforms into the *extrinsic* information utilizable for iterative decoding. The derived formula opens several starting points for optimizations, e.g. it helps to find a robust index assignment. Furthermore, it allows the conclusion that softbit-source decoding is the limiting factor if applied to iterative decoding processes. Therefore, no significant gain will be obtainable by more than two iterations. This will be demonstrated by simulation.

1. INTRODUCTION

Robust source and channel coding systems are required whenever transmission errors may occur. Speech or audio parameters determined by source coding algorithms are vulnerable to channel noise and hence bit errors in the received parameters can result in extremely annoying artifacts.

To cope with transmission errors, we recently have proposed *softbit-source decoding* by parameter estimation [1, 2] as an approach to error concealment. This approach exploits residual redundancy in the coded source parameters. In general, source codecs reduce redundancy, but due to delay and complexity constraints the source parameters will still exhibit considerable redundancy, either in terms of a non-uniform distribution or in terms of correlation.

The performance of softbit-source decoding can be further improved if channel coding algorithms add explicit redundancy at the transmitter side. At the receiver the additional information can be exploited in different ways, e.g. either by *joint* source-channel decoding [3–6] or by *iterative* source-channel decoding [7–9].

Iterative algorithms are known from the so-called *TURBO* technique originally introduced to channel decoding [10]. Two independent channel decoders are able to benefit from each other when *extrinsic* information extracted from one decoder is used as additional *a-priori* knowlegde in the other decoder in the next iteration step. In [11] it was shown that this principle can be generalized to any decoder which accepts "soft-inputs" and delivers "soft-outputs".

Therefore, it is obvious that it might be possible to apply *softbit-source decoding* to an iterative source-channel decoding scheme.

First approaches have shown by simulation [7–9] that the performance improvements seem to be limited to two iterations. In this paper, we analyzed the *extrinsic* information and show that softbitsource decoding is the limiting factor.

The paper is structured as follows. First, we briefly describe a transmission system using parameter estimation for softbit-source decoding. In Section 3, we quantify the *extrinsic* information of softbit-source decoding and identify some possible starting points for optimizations regarding softbit-source decoding in iterative decoding processes. Afterwards we introduce an approach where the parameter estimator and a simple channel decoder are concatenated. The conclusion that both decoders can benefit from each other mainly for two iterations will be demonstrated by simulations in Section 4.

2. SOFTBIT-SOURCE DECODING

For further considerations the transmission model depicted in Figure 1 is assumed.



Figure 1: Transmission model

At time instant τ a source encoder determines a continuous value u_{τ} which is individually quantized by R reproduction levels $\bar{u}^{(i)}$ with i = 1, 2, ..., R. The reproduction levels $\bar{u}^{(i)}$ are invariant with respect to τ and the whole set is given by $\mathbb{U} = \{\bar{u}^{(1)}, \bar{u}^{(2)}, ..., \bar{u}^{(R)}\}$. To each $\bar{u}^{(i)}_1$ a unique bit pattern $\mathbf{x} = \{x(1), x(2), ..., x(w)\} = x\{_1^w\}$ is assigned where the length w of \mathbf{x} is usually given by $w = \log_2(R)$. Corresponding to a set of quantizer reproduction levels \mathbb{U} , a complete set of possible bit patterns is given by \mathbb{X} . The bit pattern determined from $u_{\tau} = \bar{u}^{(i)}$ at time instant τ is denoted by $\mathbf{x} = \mathbf{x}_{\tau}$. In order to simplify the notation throughout this paper, time sequences of parameters are denoted by $\mathbf{x}_1^{\tau} = \mathbf{x}_{\tau}, \mathbf{x}_{\tau-1} \dots \mathbf{x}_1$.

At time instant τ , a bit pattern \mathbf{x}_{τ} is transmitted over a channel with additive noise n and a disturbed bit vector \mathbf{z}_{τ} is received. The task of the parameter estimation algorithm is to determine an estimate \hat{u}_{τ} of u_{τ} . Usually, the *minimum mean square error* (MMSE) is used as an optimality criterion individually for each parameter $E\{(u_{\tau} - \hat{u}_{\tau})^2\}$. $E\{\cdot\}$ denotes the expected value.

With regard to the introduced notations, the well known MMSE estimation rule can be written as

$$\hat{u}_{\tau} = \sum_{i=1}^{n} \bar{u}^{(i)} \cdot P(\bar{u}^{(i)} | \mathbf{z}_{1}^{\tau}) \quad . \tag{1}$$

¹If R is not a power of 2, w might be given by the minimum integral number $w = \lceil \log_2(R) \rceil$. In this case, Source Optimized Channel Codes [12] can benefit from the redundancy in bit mapping, $\bar{u}^{(i)} \to \mathbf{x}_{\tau}$.

 $P(\bar{u}^{(i)}|\mathbf{z}_1^{\tau})$ is the *a-posteriori* probability for reproduction level $\bar{u}^{(i)}$ when the entire history of the received bit vector \mathbf{z}_1^{τ} is given. Due to the fixed index assignment $\bar{u}^{(i)} \rightarrow \mathbf{x}_{\tau}, P(\bar{u}^{(i)}|\mathbf{z}_{1}^{\tau})$ is equal to the *i* th of *R* possible conditional probabilities $P(\mathbf{x}_{\tau} | \mathbf{z}_{1}^{\tau})$. Hence, the problem of estimating the optimal parameter value \hat{u}_{τ} can be reduced to the problem of determining the conditional probabilities $P(\mathbf{x}_{\tau} | \mathbf{z}_{1}^{\tau})$.

Suitable solutions for the determination of $P(\mathbf{x}_{\tau}|\mathbf{z}_{1}^{\tau})$ are discussed in several publications, e.g. [2], exploiting different terms of redundancy. If the redundancy due to time correlation between consecutive parameter values u_{τ} and $u_{\tau-1}$ as well as due to the non-uniform distribution of u_{τ} shall be utilized, $P(\mathbf{x}_{\tau}|\mathbf{z}_{1}^{\tau})$ can easily be determined using Bayes' Theorem and the chain rule of probability [2]

$$P(\mathbf{x}_{\tau}|\mathbf{z}_{1}^{\tau}) = C \cdot p(\mathbf{z}_{\tau}|\mathbf{x}_{\tau}) \cdot \qquad \forall \ \mathbf{x}_{\tau} \epsilon \mathbb{X}$$
$$\cdot \sum_{\mathbf{x}_{\tau-1} \epsilon \mathbb{X}} P(\mathbf{x}_{\tau}|\mathbf{x}_{\tau-1}) \cdot P(\mathbf{x}_{\tau-1}|\mathbf{z}_{1}^{\tau-1}) . \quad (2)$$

C denotes a constant term which guarantees that the sum over the conditional probability $\sum_{\mathbf{x}_{\tau} \in \mathbf{X}} P(\mathbf{x}_{\tau} | \mathbf{z}_{1}^{\tau})$ equals one. If a memoryless channel is assumed, the channel-dependent term for parameter \mathbf{x}_{τ} , $p(\mathbf{z}_{\tau}|\mathbf{x}_{\tau})$, is given in terms of single bits $x(\lambda), \prod_{\lambda=1}^{w} p(z_{\tau}(\lambda)|x_{\tau}(\lambda))$. In the second line of Eq. (2), the a-priori information resulting from the non-uniform distribution and the time correlation between consecutive parameter values u_{τ} and $u_{\tau-1}$ is given by the sum over all $P(\mathbf{x}_{\tau}|\mathbf{x}_{\tau-1})$ weighted by the a-posteriori probabilities of the previous time instant $P(\mathbf{x}_{\tau-1}|\mathbf{z}_1^{\tau-1})$. The sum reduces to the probabilities of occurrence $P(\mathbf{x}_{\tau})$ if the time correlation is neglected.

3. ITERATIVE SOURCE-CHANNEL DECODING

3.1. The Extrinsic Information of Softbit-Source Decoding As already mentioned, softbit-source decoding by parameter estimation mainly depends on the determination of a-posteriori probabilities. It is obvious that this is a soft-in/soft-out process. Channel information for single bits $p(z_{\tau}(\lambda)|x_{\tau}(\lambda))$ is combined with parameter *a-priori* knowledge $P(\mathbf{x}_{\tau}|\mathbf{x}_{\tau-1})$ or $P(\mathbf{x}_{\tau})$ to estimate parameter *a-posteriori* probabilities $P(\mathbf{x}_{\tau} | \mathbf{z}_{1}^{\tau})$. In order to quantify the gain due to softbit-source decoding for single bits, the

probabilities $P(x_{\tau}(m)|\mathbf{z}_{1}^{\tau})$ with $m = 1, 2 \dots w$ can easily be obtained by the marginal distribution of the conditional probability

of
$$P(\mathbf{x}_{\tau}|\mathbf{z}_{1}^{\tau})$$
 for $x_{\tau}(m)$

$$P(x_{\tau}(m)|\mathbf{z}_{1}^{\tau}) = \sum_{\mathbf{x}_{\tau} \in \mathbf{X}, x_{\tau}(m)} P(\mathbf{x}_{\tau}|\mathbf{z}_{1}^{\tau}) \quad . \tag{3}$$

Iterative source-channel decoding might be possible if the softoutput of the softbit-source decoder can be separated into three terms: the channel-related soft-input, the bitwise a-priori input, and an *extrinsic* value. In order to simplify the following basic considerations, we do not consider here the time correlations²i.e. we can neglect the entire history of received values, $\mathbf{z}_1^{\tau} \rightarrow \mathbf{z}_{\tau}$, and in addition the sum in Eq. (2) reduces to the probabilities of

²The presented basic considerations can easily be extended to the case considering the non-uniform distribution as well as time dependencies.

occurence $P(\mathbf{x}_{\tau})$. Applying the simplified description of Eq. (2) in Eq. (3), $P(x_{\tau}(m)|\mathbf{z}_{\tau})$ is given by

$$P(x_{\tau}(m)|\mathbf{z}_{\tau}) = \sum_{\mathbf{x}_{\tau} \in \mathbf{X}, x_{\tau}(m)} C \cdot p(\mathbf{z}_{\tau}|\mathbf{x}_{\tau}) \cdot P(\mathbf{x}_{\tau}) .$$
(4)

Furthermore, to determine each of the three terms, channelrelated input, bitwise a-priori input and extrinsic value as shown below, we re-write Eq. (4) in log-likelihood algebra for single bits.

If a binary random variable takes on the value $x_{\tau}(m) \in \{0, 1\}$ and if it is conditioned on z_{τ} , then the log-likelihood ratio [11] is defined as

$$L(x_{\tau}(m)|\mathbf{z}_{\tau}) = \log \frac{P(x_{\tau}(m) = 0|\mathbf{z}_{\tau})}{P(x_{\tau}(m) = 1|\mathbf{z}_{\tau})}$$
(5)

with log representing the natural logarithm.

Substituting $P(x_{\tau}(m) = 0 | \mathbf{z}_{\tau})$ and $P(x_{\tau}(m) = 1 | \mathbf{z}_{\tau})$ by the marginal distribution of the conditional probabilities given in (4) results in

$$L(x_{\tau}(m)|\mathbf{z}_{\tau}) = \log \frac{\sum_{\mathbf{x}_{\tau} \in \mathbf{X}, \atop \mathbf{x}_{\tau} \in \mathbf{X}, = 0} P(\mathbf{x}_{\tau}) \cdot p(\mathbf{z}_{\tau}|\mathbf{x}_{\tau})}{\sum_{\substack{\mathbf{x}_{\tau} \in \mathbf{X}, \\ \mathbf{x}_{\tau} (\mathbf{m}) = 1}} P(\mathbf{x}_{\tau}) \cdot p(\mathbf{z}_{\tau}|\mathbf{x}_{\tau})} \quad .$$
(6)

The marginal distribution in the numerator has to be determined for all $\mathbf{x}_{\tau} \in \mathbb{X}$ under the condition $x_{\tau}(m) = 0$, and in the denominator for all $\mathbf{x}_{\tau} \in \mathbb{X}$ with $x_{\tau}(m) = 1$, respectively. In case of a memoryless transmission channel the channel-dependent parameter term $p(\mathbf{z}_{\tau}|\mathbf{x}_{\tau})$ is given by a product of terms for single bits

$$L(x_{\tau}(m)|\mathbf{z}_{\tau}) = \log \frac{\sum\limits_{\substack{\mathbf{x}_{\tau} \in \mathbf{X}, \\ x_{\tau}(m)=0}} P(\mathbf{x}_{\tau}) \cdot \prod\limits_{\lambda=1}^{w} p(z_{\tau}(\lambda)|x_{\tau}(\lambda))}{\sum\limits_{\substack{\mathbf{x}_{\tau} \in \mathbf{X}, \\ x_{\tau}(m)=1}} P(\mathbf{x}_{\tau}) \cdot \prod\limits_{\lambda=1}^{w} p(z_{\tau}(\lambda)|x_{\tau}(\lambda))} .$$
(7)

As $p(z_{\tau}(\lambda)|x_{\tau}(\lambda))$ with $\lambda = m$ is equal for all elements under the sums, both in the numerator and in the denominator, it can be factored as $L(z_{\tau}(m)|x_{\tau}(m))$,

$$L(x_{\tau}(m)|\mathbf{z}_{\tau}) = L(z_{\tau}(m)|x_{\tau}(m)) + \sum_{\substack{\mathbf{x}_{\tau} \in \mathbf{X}, \\ \lambda \neq m}} P(\mathbf{x}_{\tau}) \cdot \prod_{\substack{\lambda=1, \\ \lambda \neq m}}^{w} p(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\mathbf{x}_{\tau} \in \mathbf{X}, \\ x_{\tau}(m)=1}} P(\mathbf{x}_{\tau}) \cdot \prod_{\substack{\lambda=1, \\ \lambda \neq m}}^{w} p(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(\mathbf{x}_{\tau}) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(\mathbf{x}_{\tau}) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(z$$

Furthermore, the *a*-priori information of parameter \mathbf{x}_{τ} is a joint probability $P(x_{\tau} \{ {}^w_1 \})$ of single bits $x_{\tau}(\lambda)$ with $\lambda = 1, 2, \ldots, w$. Applying the chain rule allows to extract the probability for $P(x_{\tau}(m)),$

$$P(\mathbf{x}_{\tau} = x_{\tau} \{ {}^w_1 \}) = P(x_{\tau} \{ {}^{m-1}_1 \}, x_{\tau} \{ {}^w_{m+1} \} | x_{\tau}(m)) \cdot P(x_{\tau}(m))$$

The term $P(x_{\tau}(m))$ of $P(\mathbf{x}_{\tau})$ in (8) is equal for all elements under the sum, hence it can be separated as bitwise a-priori information $L(x_{\tau}(m))$. The final result is given by Eq. (9). The soft-output of softbit-source decoding can be split into three independent terms: the channel-related soft-input $L(z_{\tau}(m)|x_{\tau}(m))$,

w

Bitwise representation of the soft-output of softbit-source decoding:

$$L(x_{\tau}(m)|\mathbf{z}_{\tau}) = L(z_{\tau}(m)|x_{\tau}(m)) + L(x_{\tau}(m)) + \log \frac{\sum_{\substack{\mathbf{x}_{\tau} \in \mathbf{X}, \\ x_{\tau}(m) = 0}} P(x_{\tau}\{_{1}^{m-1}\}, x_{\tau}\{_{m+1}^{w}\}|x_{\tau}(m) = 0) \cdot \prod_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} p(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(x_{\tau}\{_{1}^{m-1}\}, x_{\tau}\{_{m+1}^{w}\}|x_{\tau}(m) = 1) \cdot \prod_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} p(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}} P(x_{\tau}\{_{1}^{m-1}\}, x_{\tau}\{_{m+1}^{w}\}|x_{\tau}(m) = 1) \cdot \prod_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} p(z_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}\{_{1}^{m-1}\}, x_{\tau}\{_{1}^{w}\}|x_{\tau}(m) = 1) \cdot \prod_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}\{_{1}^{m-1}\}, x_{\tau}\{_{1}^{w}\}|x_{\tau}(m) = 1) \cdot \prod_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}\{_{1}^{m-1}\}, x_{\tau}\{_{1}^{w}\}|x_{\tau}(m) = 1) \cdot \prod_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}\{_{1}^{w}\}|x_{\tau}(m) = 1) \cdot \prod_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}\{_{1}^{w}\}|x_{\tau}(m) = 1) \cdot \prod_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{\substack{\lambda = 1, \\ \lambda \neq m}}^{w} P(x_{\tau}(\lambda)|x_{\tau}(\lambda)) - \sum_{$$

the bitwise *a*-priori information $L(x_{\tau}(m))$, and an *extrinsic* part $L_e^{SBSD}(x_{\tau}(m))$ resulting from softbit-source decoding (SBSD). The *extrinsic* part in (9) is given by the last term and it consists of channel information as well as joint *a*-priori knowledge for the bits representing parameter \mathbf{x}_{τ} excluding bit $x_{\tau}(m)$ itself. It is easy to prove that the parameter *a*-priori knowledge $P(x_{\tau}\{{}^{m-1}_{1}\}, x_{\tau}\{{}^{w}_{m+1}\}|x_{\tau}(m))$ has to be replaced by

$$\sum_{\mathbf{x}_{\tau-1}\in\mathbf{X}} P(x_{\tau}\{{}^{m-1}_{1}\}, x_{\tau}\{{}^{w}_{m+1}\}|x_{\tau}(m), \mathbf{x}_{\tau-1}) \cdot P(\mathbf{x}_{\tau-1}|\mathbf{z}_{1}^{\tau-1})$$

if in addition time correlation is considered. In this case the *a-posteriori* log-likelihood $L(x_{\tau}(m)|\mathbf{z}_{\tau})$ transforms into $L(x_{\tau}(m)|\mathbf{z}_{\tau}^{T})$. Furthermore, if necessary the bit transition pdfs $p(z_{\tau}(\lambda)|x_{\tau}(\lambda))$ can also be expressed in log-likelihood values $L(z_{\tau}(\lambda)|x_{\tau}(\lambda))$ similar to Eq. (5).

3.2. Possible Starting Points to Maximize $L(x_{\tau}(m)|\mathbf{z}_{\tau})$

If the highest additional information for the bits $x_{\tau}(m)$ should be obtained, the *a-posteriori* log-likelihood values $L(x_{\tau}(m)|\mathbf{z}_{\tau})$ or $L(x_{\tau}(m)|\mathbf{z}_{1}^{T})$ with m = 1, 2...w have to be maximized. One possibility for such a maximization is given by a re-arrangement of the *a-priori* probabilities $P(\mathbf{x}_{\tau})$. As a re-arrangement has influence on the bitwise *a-priori* knowledge $L(x_{\tau}(m))$ and the *extrinsic* information $L_{e}^{SBSD}(x_{\tau}(m))$, both terms of Eq. (9) have to be taken into account. This joint optimization can be performed as well when the last term of Eq. (8) is considered instead. In Eq. (8) the ratio of sums over weighted *a-priori* probabilities determines how much additional information will be utilizable. For example, in case of a noisefree transmission channel there is only one product of bit transition pdfs $\prod_{\lambda=1,\lambda\neq m}^{w} p(z_{\tau}(\lambda)|x_{\tau}(\lambda))$ unequal to 0, i.e. the highest possible amount of additional information $|L_{E_{h}/N_{0}\to\infty}(x_{\tau}(m))|$ for $x_{\tau}(m)$ is therefore given by

$$|L_{E_b/N_0 \to \infty}(x_\tau(m))| = \log \frac{\max_{\forall \mathbf{x}_\tau} \{P(\mathbf{x}_\tau)\}}{\min_{\forall \mathbf{x}_\tau} \{P(\mathbf{x}_\tau)\}}$$

Indeed, taking transmission errors into account might be the much more interesting case. Hence, to give a rough approximation for a suitable index assignment, we consider the transmission over a heavily disturbed channel. In this extreme case all products over bit transition pdfs $p(z_{\tau}(\lambda)|x_{\tau}(\lambda))$ are equally likely and therefore cancel out. The additional information $L_{E_b/N_0 \rightarrow -\infty}(x_{\tau}(m))$ provided by the bitwise *a-priori* knowledge as well as the *extrinsic* information can be approximately expressed as

$$L_{E_b/N_0\to-\infty}(x_{\tau}(m)) = \log \frac{\sum_{\mathbf{x}_{\tau}\in\mathbb{X}, x_{\tau}(m)=0} P(\mathbf{x}_{\tau})}{\sum_{\mathbf{x}_{\tau}\in\mathbb{X}, x_{\tau}(m)=1} P(\mathbf{x}_{\tau})}.$$

Table 1 gives an example with obtainable $L_{E_b/N_0 \to -\infty}(x_{\tau}(m))$ for a given *a-priori* knowledge $P(\mathbf{x}_{\tau})$ with w = 3 bit and different index assignments. It shows that for a symmetrical distribution the *folded binary* index assignment outperforms the *natural binary* as well as the *Gray encoded* bit mapping because higher $L_{E_b/N_0 \to -\infty}(x_{\tau}(m))$ are obtained. Therefore and for reasons

	<i>a-priori</i> probabilities $P(\mathbf{x}_{\tau})$	
	0.04 0.10 0.16 0.20 0.20 0.16 0.10 0.04	
IA	bit pattern: $x_{\tau}(1)x_{\tau}(2)x_{\tau}(3)$	$L_{-\infty}(x_{\tau}(m))$
nb	000 001 010 011 100 101 110 111	0.0 0.0 0.0
gc	000 001 011 010 110 111 101 100	0.0 0.94 0.08
fb	011 010 001 000 100 101 110 111	0.0 0.94 0.41

Table 1: Example of $L_{E_b/N_0 \to -\infty}$ with different index assignments (IA): natural bin.(nb), folded bin.(fb), Gray cod.(gc)

given in [6, 13], in the simulations presented in Sec. 4 the folded

binary bit mapping is applied. Of course, also folded binary seems to be a suboptimal bit mapping as there is no additional value $L_{E_b/N_0 \to -\infty}(x_\tau(m))$ available for bit $x_\tau(1)$. Hence, even better results might be achievable if the last term in Eq. (8) is transformed into a cost function and the index assignment optimized as in [14].

3.3. Utilizing the *Extrinsic* Information in an Iterative Process The *extrinsic* information of softbit-source decoding as quantified in Sec. 3.1 is utilizable in an iterative process. One possible application is iterative source-channel decoding as depicted in Fig. 2. The transmission system introduced in Sec. 2 is extended by chan-



Figure 2: Iterative source-channel decoding

nel en-/decoding blocks. Furthermore, if source and channel decoding shall be performed iteratively it has to be guaranteed that both steps are independent from each other. Therefore, in addition to Fig. 1 it is assumed that at time instant τ the source encoder determines a set of N parameters $\underline{u}_{\tau} = \{u_{\tau,1}, u_{\tau,2} \dots u_{\tau,N}\}$. Each $u_{\tau,\kappa}$ is quantized individually and to each quantizer reproduction level a unique bit pattern $\mathbf{x}_{\tau,\kappa}$ is assigned. The complete set \underline{u}_{τ} corresponds to a set of bit patterns $\underline{\mathbf{x}}_{\tau}$.

After transmission of the channel-encoded set $\underline{\mathbf{y}}_{\tau}$ over a channel with additive noise n, a possibly disturbed set of bit patterns $\underline{\mathbf{q}}_{\tau}$ is received. The required independence of source and channel decoding ensures that the overall log-likelihood $L(x_{\tau,\kappa}(m)|\underline{\mathbf{q}}_{1}^{\tau})$ can be separated into

$$L(x_{\tau,\kappa}(m)|\underline{\mathbf{q}}_{1}^{\tau}) = L(x_{\tau,\kappa}(m)|\mathbf{z}_{1,\kappa}^{\tau}) + L_{e}^{CD}(x_{\tau,\kappa}(m)), \quad (10)$$

i.e. into an *extrinsic* value $L_e^{CD}(x_{\tau,\kappa}(m))$ from the channel decoder (CD) as well as an *a-posteriori* log-likelihood of softbit-source decoding similar to Eq. (9).

As softbit-source decoding always exploits the entire history of received bit patterns $z_{1,\kappa}^{\tau}$ for a fixed κ , independence might be ensured if channel coding is performed over different κ with $\kappa = 1, 2...N$. One possible approach using a simple parity check code is given in Sec. 4.

4. SIMULATION RESULTS

For simulation each parameter $u_{\tau,\kappa}$ is modelled individually by a Gauss-Markov process of the order one. For this, white Gaussian noise is processed by a first-order recursive filter and afterwards normalized to $\sigma^2_{u_{\tau,\kappa}} = 1$. The filter coefficient allows to adjust auto-correlation properties, e.g. $\rho = 0.95$. Different parameters $u_{\tau,\kappa}$, $u_{\tau,\kappa}$ ($\kappa \neq \hat{\kappa}$) within one set \underline{u}_{τ} are statistically independent. The parameters $u_{\tau,\kappa}$ are individually quantized by an 8-level Lloyd-Max quantizer using w = 3 bits. Furthermore, a set of parameters \underline{u}_{τ} consists of N = 3 entries $u_{\tau,\kappa}$ with $\kappa = 1, \ldots N$. For index assignment, folded binary is applied as discussed in Sec. 3.2.

Channel encoding is performed by a simple single parity check code over the index of position κ . For each bit index $m, m = 1, \ldots w$ an even parity bit $\pi_{\tau}(m)$ is generated by $\pi_{\tau}(m) = \{u_{\tau,1}(m) \oplus u_{\tau,2}(m) \oplus \ldots u_{\tau,N}(m)\}$ with \oplus representing the binary *exclusive-or* operation. Finally, the overall code rate is given by $r = \frac{N \cdot w}{(N+1) \cdot w}$ and the encoded set of bit patterns \underline{y}_{τ} will have a systematic form $\underline{y}_{\tau} = \{\underline{x}_{\tau}, \pi_{\tau}\}$. As transmission channel serves an AWGN channel with known E_b/N_0 .

At the receiver side decoding will be done iteratively in two independent steps. In each iteration the extrinsic information of the one decoder will be used as additional *a-priori* knowledge by the other one. For the first iteration all *extrinsic* values of softbit-source decoding $L_e^{SBSD}(x_{\tau,\kappa}(m))$ with $\kappa = 1...N$ and $m = 1 \dots w$ are initialized with zeros. The first step channel decoding is performed according to [11] and the second step softbit-source decoding is done as discussed in Sec. 3. The updated extrinsic value of softbit-source decoding is fed back for different numbers of iterations. After the last iteration the *a-posteriori* log-likelihoods $L(x_{\tau,\kappa}(m)|\mathbf{q}_1^{\tau})$ for single bits are transformed into parameter *a*-posteriori probabilities $P(\mathbf{x}_{\tau,\kappa}|\mathbf{q}_1^{\tau})$ by inverting Eq. (3) and (5). The marginal distribution of Eq. (3) can be re-calculated by $\prod_{\lambda=1}^{w} P(x_{\tau,\kappa}(\lambda)|\underline{q}_{1}^{\tau})$ if independence of the single $P(x_{\tau,\kappa}(\lambda)|\mathbf{q}_{\tau})$ is assumed. Finally, $P(\mathbf{x}_{\tau,\kappa}|\mathbf{q}_{\tau})$ is inserted in the MMSE estimation rule given by Eq. (1). Fig. 3 depicts the parameter signal-to-noise ratio (SNR) for simulations with different numbers of iterations.



Figure 3: Simulation result for different numbers of iterations if SBSD is concatenated with a single parity check code

The curve labelled with "0. iteration" neglects channel decoding and softbit-source decoding. The desired parameters $\hat{u}_{\tau,\kappa}$ are directly estimated by exploiting the corresponding received bit patterms $\mathbf{q}_{\tau,\kappa}$. If in the first step channel decoding is carried out (see "0⁺ iteration" in Fig. 3), the *extrinsic* value $L_e^{CD}(x_{\tau,\kappa}(m))$ is utilizable for each bit $x_{\tau,\kappa}(m)$. This results in a gain of several dB for the parameter SNR for moderate E_b/N_0 . Next, the "1. iteration" will be completed, when in addition the *extrinsic* value of softbit-source decoding $L_e^{SBSD}(x_{\tau,\kappa}(m))$ is taken into account. Due to the high auto-correlation factor of $\rho = 0.95$, the parameter SNR can further be improved by up to 6.1 dB. When the next iteration is started and the updated $L_e^{SBSD}(x_{\tau,\kappa}(m))$ is used as additional a-priori knowledge, the channel decoder can benefit from the new information ("1⁺, *iteration*"). A slight increase in quality of about 0.51 dB is noticable. But afterwards, when the "2. iteration" is completed the softbit-source decoder seems not to be able to take advantage of the updated extrinsic value of the channel decoder. There is no considerable gain. More than 2 iterations do not increase the parameter SNR any further.

It seems to be that the softbit-source decoder is the limiting factor. Improving the softbit-source decoder's additional *a-priori* knowledge, i.e. an update of the channel decoder's *extrinsic* value $L_e^{CD}(x_{\tau,\kappa}(m))$, does not enable the softbit-source decoder to enhance the overall quality. An explanation might be possible if the determination rule for $L_e^{BBSD}(x_{\tau,\kappa}(m))$ given

in Eq. (9) is considered. It turns out that the weighted sums of $L_{e}^{SBSD}(x_{\tau,\kappa}(m))$ are robust against minor variations in the transition pdfs $p(z_{\tau}(\lambda)|x_{\tau}(\lambda))$. Furthermore, in this case the *extrinsic* value of softbit-source decoding is approximately constant. Therefore, usually no improvements are achievable for more than 1⁺ iteration. Similar results are also obtained with different auto-correlation factors ρ .

5. CONCLUSION

In this paper we applied softbit-source decoding to an iterative source-channel decoding approach. As a novelty, we quantified the *extrinsic* value of softbit-source decoding. The derived formula for the *extrinsic* information makes it possible to find a robust index assignment that increases quality. But furthermore, the rule offers also the possibility to remark that softbit-source decoding is the limiting factor if applied in an iterative process. Simulations have shown that minor variations in the softbit-source decoder's input usually have a neglectable influence on the softbit-source decoding can benefit from stronger channel codes which might provide larger variations in the pdfs $p(z_{\tau}(\lambda)|x_{\tau}(\lambda))$.

6. ACKNOWLEDGEMENT

The authors would like to thank Sascha Amft, Stefan Heinen, and especially Jean-Marc Picard for many inspiring discussions.

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