JOINT SOURCE-CHANNEL MMSE-DECODING OF SPEECH PARAMETERS

Stefan Heinen and Peter Vary

Institute of Communication Systems and Data Processing (ind)
Aachen University of Technology
heinen@ind.rwth-aachen.de, vary@ind.rwth-aachen.de

ABSTRACT

For speech transmission in digital land mobile telephony, effective compression algorithms have to be used to achieve a high bandwidth efficiency. Furthermore, a variety of adverse transmission effects make it necessary to employ powerful error control techniques to keep bit error rates tolerable low and thus to guarantee a high speech quality.

Speech compression is designed to remove irrelevancy and redundancy from the speech signal. Yet measuring the statistical properties of speech parameters extracted by practical compression schemes shows, that a considerable amount of redundancy still remains, either in terms of non-uniform distribution or due to time-correlation of parameters extracted from subsequent speech segments.

In this contribution, we propose a new *Minimum Mean Square Error* (MMSE) decoder for block-oriented trellis codes, that is able to exploit the time-correlation of subsequent parameter sets. The decoder yields non-discrete speech parameter *Mean Square* (MS) estimates. Thus it combines two recently published approaches to exploit residual redundancy: *Source Controlled Channel Decoding* (SCCD) [1] and *Soft Bit Source Decoding* (SBSD) [2] in one algorithm.

1. INTRODUCTION

Speech coding is indispensable to achieve a required bandwidth efficiency in applications where bandwidth is a limited resource, as e.g. in digital mobile telecommunications. In contrast to fixed network transmission, the mobile radio channel suffers from a variety of adverse effects such as multi-path propagation and Doppler spread which require a combination of interleaving, channel coding and equalization to achieve tolerable bit error rates and good speech quality, respectively.

Especially at high compression rates (e.g. 0.5-1.5 bits per speech sample), which are achieved by modern CELP codecs, the compressed speech data becomes extremely vulnerable. Therefore, in current mobile systems powerful *Forward Error Correction* (FEC) schemes, usually based on convolutional codes, are applied for error protection.

In spite of the data compression algorithms applied to the speech signal, the stream of speech parameters produced by practical encoders still exhibit considerable redundancy. As speech is highly instationary, in practice it is impossible to remove redundancy completely. Hence, if redundancy is unavoidable, it might be promising to exploit it at the receiver to enhance the disturbed signal, as already indicated by Shannon in his famous paper [3].

Actually, there are several recent publications describing methods to exploit residual redundancy. Mainly two approaches are propagated: One way is to utilize residual redundancy to support channel decoding, which leads to *Source Controlled Channel Decoding* (SCCD) either on bit level [1] or on parameter level [4, 5, 6]. A drawback of these techniques is their detection rule: as they are based on *Maximum A Posteriori* (MAP) decision, they minimize the bit error rate and are only sub-optimal in the MMSE sense. Another approach exploits residual redundancy in terms of *Soft Bit Source Decoding* (SBSD) [2]. Reliability information gained from a soft-output channel decoder [7, 8] is combined with the *a priori* knowledge to estimate the parameters.

In this contribution, we investigate the interesting question, if both approaches can be concatenated. However, this would imply to exploit *a priori* information twice, in the channel decoding and in the source decoding stage. To examine if this is possible, we make a twofold approach. On one hand we study the performance of the concatenation by simulation, on the other we develop the MSE-optimal decoder for convolutionally encoded Markovian speech parameters. The latter affirms the conjecture that at least for optimal decoding it is sufficient to use *a priori* information only once.

The rest of the paper is structured as follows: First, we abstract from the speech compression process by modeling the sequence of speech parameters as a Markov chain. A description of the considered channel code and transmission channel is given in Section 3 and 4, respectively. In Section 5 we present the new optimal decoding algorithm. Simulation results comparing the performance of SCCD, SBSD and the new MMSE approach are given in Section 6.

2. SOURCE MODEL

Measurements of the statistical properties of speech parameters extracted by block-oriented speech compression schemes show, that there is usually only low correlation between different-type parameters extracted from the same speech segment and comparatively high correlation in parameters of same type which are extracted from subsequent speech segments. Additionally, due to the usage of MSE-optimum quantizers, the probability of occurrence of different reproduction levels is in general non-uniform.

These observations inspire the speech encoder model shown in Figure 1. Without loss of generality, we assume that N scalar parameters are extracted from a speech segment. We represent each speech parameter $u_{i,\tau}$ by a scalar i.i.d. source with pdf $p_{\tilde{u}_i}$ and a subsequent linear filter $u_{\tau,i} = f_i(\tilde{u}_{\tau,i}, .., \tilde{u}_{\tau-L_i,i})$, where L_i is the memory length of filter f_i. The continuous parameter values $u_{\tau,i}$ are individually quantized by Q_i. The $\bar{u}_{\tau,i}$ take values in the reproduction sets $\mathbb{U}_i = \{\bar{u}_i^{(1)}, .., \bar{u}_i^{(R_i)}\}$, with R_i the number of

0-7803-6293-4/00/$10.00 ©2000 IEEE.

reproduction levels of quantizer Q_i. To each reproduction level a unique index (bit code) $x_{\tau,i} \in \mathbb{X}_i = \{x_i^{(1)}, .., x_i^{(R_i)}\}$ is assigned.

The length w_i of bit code $x_{\tau,i}$ is given by $w_i = \lceil \log_2(R_i) \rceil$, i.e. the minimum integral number of bits required to code R_i symbols. If the number of reproduction levels R_i is not a power of two (e.g., if the system's accuracy specification is already fulfilled by a quantizer having $R_i < 2^{w_i}$ reproduction levels), we can exploit the inherent redundancy of the mapping $\bar{u}_{\tau,i} \to x_{\tau,i}$ for a parameter-individual error protection in terms of *Source Optimized Channel Codes* [9, 10, 11]. The codes are composed to a bit vector $\mathbf{x}_\tau$, where $\mathbf{x}_\tau \in \mathbb{X} = \{\mathbf{x}^{(1)}, .., \mathbf{x}^{(R)}\}$, $R = \prod_i R_i$ and forwarded to the channel encoder. To simplify notation, we write also other vectors as boldface characters, e.g. $\mathbf{u}_\tau = (u_{\tau,1}, .., u_{\tau,N})$.

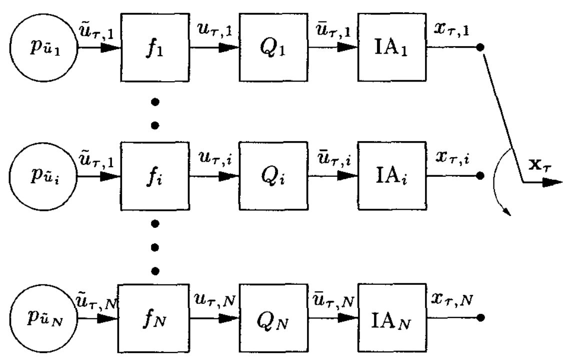

Figure 1: Model of speech parameter generation
f_i: linear filter, Q_i: quantizer, IA_i: index assignment

Due to the filtering of $\tilde{u}_{\tau,i}$, the bit vectors $\mathbf{x}_\tau$ exhibit Markovity, i.e. denoting the random bit vector at time instant τ by $\mathbf{X}_\tau$ we get[1]

$$\begin{aligned}\Pr\{\mathbf{X}_\tau = \mathbf{x}_\tau \,|\, \mathbf{X}_{\tau-1} = \mathbf{x}_{\tau-1}, .., \mathbf{X}_1 = \mathbf{x}_1\} &= \\ \Pr\{\mathbf{X}_\tau = \mathbf{x}_\tau \,|\, \mathbf{X}_{\tau-1} = \mathbf{x}_{\tau-1}, .., \mathbf{X}_{\tau-L} = \mathbf{x}_{\tau-L}\}&\ , \end{aligned} \quad (1)$$

with $L = \max_i L_i$. Furthermore, the components of $\mathbf{X}_\tau$, which will denoted by $X_{\tau,i}$, are statistically independent

$$\Pr\{\mathbf{X}_\tau = \mathbf{x}_\tau\} = \prod_i \Pr\{X_{\tau,i} = x_{\tau,i}\} \ . \quad (2)$$

To keep equations readable, in the rest of the paper we will use the notation $P(\mathbf{x}_\tau) := \Pr\{\mathbf{X}_\tau = \mathbf{x}_\tau\}$ unless ambiguity requires the more detailed style.

3. CHANNEL CODE

We consider a memory M convolutional code that maps a bit vector $\mathbf{x}_\tau = (x_{\tau,1}, .., x_{\tau,N})$ to a codeword $\mathbf{y}_\tau = (y_{\tau,1}, .., y_{\tau,N})$, as shown in Figure 2. For reasons of simplicity, we assume a constant coding rate of k/m. Hence, by feeding a bit code $x_{\tau,i}$ consisting of w_i bits into the channel encoder, we obtain a sequence of $\frac{m}{k} \cdot w_i$ coded bits $y_{\tau,i}$. Hence, the only constraint on the coder structure is w_i/k being an integer. Due to the memory of the convolution, $y_{\tau,i}$ is a deterministic function of both the index bits $x_{\tau,i}$ and the encoder's state $S_i \in \{1, .., 2^M\}$,

[1] This is exactly fulfilled only if the filters have IIR.

which also applies to the subsequent state S_{i+1}. Thus the channel coder is uniquely described by the functions

$$y_{\tau,i} = \mathcal{F}_y(S_i, S_{i+1}) \quad \text{and} \quad S_{i+1} = \mathcal{F}_S(S_i, x_{\tau,i}) \ , \quad (3)$$

or from a probabilistic point of view

$$P(y \,|\, S_i, S_{i+1}) = \begin{cases} 1 & y = \mathcal{F}_y(S_i, S_{i+1}) \\ 0 & y \neq \mathcal{F}_y(S_i, S_{i+1}) \end{cases} \quad (4)$$

$$P(s \,|\, S_i, x_{\tau,i}) = \begin{cases} 1 & s = \mathcal{F}_S(S_i, x_{\tau,i}) \\ 0 & s \neq \mathcal{F}_S(S_i, x_{\tau,i}) \ . \end{cases} \quad (5)$$

4. TRANSMISSION CHANNEL

Figure 2 depicts the considered transmission model. We assume a stationary memoryless additive noise process with i.i.d. components, described by the pdf

$$p_\mathbf{n}(\mathbf{n}) = \prod_i p_n(n_i) \ . \quad (6)$$

Hence, we can uniquely characterize the transmission channel by the conditional pdf $p(\mathbf{z}_\tau \,|\, \mathbf{y}_\tau) = p_\mathbf{n}(\mathbf{z}_\tau - \mathbf{y}_\tau)$.

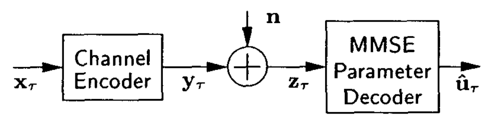

Figure 2: Transmission model

5. MMSE PARAMETER DECODER

As Figure 2 indicates, the task of the decoder is not to decode a sequence of bits, but to gain MMSE-optimal parameter estimates $\hat{\mathbf{u}}_\tau$ from the noisy observation vector $\mathbf{z}_\tau$. To do so, we have to take into account that the source is not white and thus the estimate $\hat{\mathbf{u}}_\tau$ at instant τ depends on the entire history[2] of received vectors, i.e. $\hat{\mathbf{u}}_\tau = \hat{\mathbf{u}}_\tau(\mathbf{z}_1, .., \mathbf{z}_\tau)$.

The MSE D is given by the expectation of $\|\mathbf{u}_\tau - \hat{\mathbf{u}}_\tau\|^2$ over all random variables the expression depends on, hence

$$D = \int_{\mathbf{z}_1} .. \int_{\mathbf{z}_\tau} \int_{\mathbf{u}_\tau} \|\mathbf{u}_\tau - \hat{\mathbf{u}}_\tau\|^2 p(\mathbf{u}_\tau, \mathbf{z}_1^\tau) \, d\mathbf{u}_\tau \, d\mathbf{z}_1 .. d\mathbf{z}_\tau \ , \quad (7)$$

where we use the notation $\mathbf{z}_1^\tau := (\mathbf{z}_1, .., \mathbf{z}_\tau)$ to denote the sequence of observed vectors (and later accordingly for other sequences). It is well known that minimizing D leads to the conditional expectation [12]

$$\hat{u}_{\tau,i} = \frac{1}{p(\mathbf{z}_1^\tau)} \int_{u_{\tau,i}} u_{\tau,i} \, p(u_{\tau,i}, \mathbf{z}_1^\tau) \, du_{\tau,i} \ . \quad (8)$$

If we expand the pdf in (8) to

$$p(u_{\tau,i}, \mathbf{z}_1^\tau) = \sum_{\ell=1}^{R_i} p(\mathbf{z}_1^\tau \,|\, x_i^{(\ell)}) \, p(x_i^{(\ell)} \,|\, u_{\tau,i}) \, p(u_{\tau,i}) \quad (9)$$

[2] Actually, it also depends on future observation vectors. However, to exploit these dependencies, additional delay would be necessary, which is usually prohibitive in case of a real-time speech transmission. For this reason we do not consider dependencies on future observations here, yet the extension of the presented algorithm to this case is straightforward.

and note that $p(x_i^{(\ell)} \mid u_{\tau,i})=1$ if $u_{\tau,i} \in \mathbb{C}_i^{(\ell)}$ and 0 else, where $\mathbb{C}_i^{(\ell)}$ is the ℓ-th cell of quantizer Q_i, we get

$$\hat{u}_{\tau,i} = \frac{1}{p(\mathbf{z}_1^\tau)} \sum_{\ell=1}^{R_i} p(\mathbf{z}_1^\tau \mid x_i^{(\ell)}) \int_{u_{\tau,i} \in \mathbb{C}_i^{(\ell)}} u_{\tau,i}\, p(u_{\tau,i})\, du_{\tau,i} \,. \tag{10}$$

If we assume without loss of generality that the reproduction levels $\bar{u}_i^{(\ell)}$ are centroids of their respective cells, i.e.

$$\bar{u}_i^{(\ell)} = \frac{1}{\Pr\{u_{\tau,i} \in \mathbb{C}_i^{(\ell)}\}} \int_{u_{\tau,i} \in \mathbb{C}_i^{(\ell)}} u_{\tau,i}\, p(u_{\tau,i})\, du_{\tau,i} \tag{11}$$

and take into account that $\Pr\{u_{\tau,i} \in \mathbb{C}_i^{(\ell)}\} = P(x_i^{(\ell)})$, we finally obtain the optimal estimator

$$\hat{u}_{\tau,i} = \frac{1}{p(\mathbf{z}_1^\tau)} \sum_{\ell=1}^{R_i} \bar{u}_i^{(\ell)}\, p(x_i^{(\ell)}, \mathbf{z}_1^\tau) \,. \tag{12}$$

As (12) shows, the MMSE-optimal decoding problem mainly consists in determining the value of the joint pdf $p(x_i^{(\ell)}, \mathbf{z}_1^\tau)$ for each $x_i^{(\ell)}$. The formal solution is given by the marginal distribution

$$p(x_i^{(\ell)}, \mathbf{z}_1^\tau) = \sum_{\mathbf{x}_1^\tau \in \mathbb{X},\ x_{\tau,i}=x_i^{(\ell)}} p(\mathbf{x}_1^\tau, \mathbf{z}_1^\tau) \,, \tag{13}$$

which of course is far to complex for a practical implementation. To find a recursion, we expand the joint pdf under the sum to

$$p(\mathbf{x}_1^\tau, \mathbf{z}_1^\tau) = p(\mathbf{z}_\tau \mid \mathbf{x}_1^\tau, \mathbf{z}_1^{\tau-1}) \cdot \\ \cdot\, p(\mathbf{x}_\tau \mid \mathbf{z}_1^{\tau-1}, \mathbf{x}_1^{\tau-1})\, p(\mathbf{x}_1^{\tau-1}, \mathbf{z}_1^{\tau-1}) \,. \tag{14}$$

By exploiting that the channel is memoryless and due to the Markov property of the source, we obtain

$$p(\mathbf{x}_1^\tau, \mathbf{z}_1^\tau) = p(\mathbf{z}_\tau \mid \mathbf{x}_\tau)\, P(\mathbf{x}_\tau \mid \mathbf{x}_{\tau-L}^{\tau-1})\, p(\mathbf{x}_1^{\tau-1}, \mathbf{z}_1^{\tau-1}) \,. \tag{15}$$

Before returning to (13), we first consider the computation of $p(\mathbf{x}_{\tau-L+1}^\tau, \mathbf{z}_1^\tau)$, which is given by the recursion formula

$$p(\mathbf{x}_{\tau-L+1}^\tau, \mathbf{z}_1^\tau) = p(\mathbf{z}_\tau \mid \mathbf{x}_\tau) \cdot \\ \cdot \sum_{\mathbf{x}_{\tau-L} \in \mathbb{X}} P(\mathbf{x}_\tau \mid \mathbf{x}_{\tau-L}^{\tau-1})\, p(\mathbf{x}_{\tau-L}^{\tau-1}, \mathbf{z}_1^{\tau-1}) \,. \tag{16}$$

The starting point of this recursion is determined by the initial states of the linear filters f_i. Equation (16) has to be initialized with the *a priori* probability of the sequence $\mathbf{x}_1^{L-1}$, thus we formally define $p(\mathbf{x}_{-L+1}^0, \mathbf{z}_1^0) := P(\mathbf{x}_1^{L-1})$.

Furthermore, due to the mutual independence of the components of $\mathbf{x}_\tau$, we can factorize the sum in (16), which yields

$$p(\mathbf{x}_{\tau-L+1}^\tau, \mathbf{z}_1^\tau) = C\, p(\mathbf{z}_\tau \mid \mathbf{x}_\tau) \cdot \\ \cdot \prod_{j=1}^{N} \underbrace{\sum_{x_{\tau-L,j} \in \mathbb{X}_j} P(x_{\tau,i} \mid x_{\tau-L,j}^{\tau-1})\, p(x_{\tau-L,j}^{\tau-1}, \mathbf{z}_1^{\tau-1})}_{=p(x_{\tau-L+1,j}^\tau, \mathbf{z}_1^{\tau-1})} \,, \tag{17}$$

where $x_{\tau-L,i}^{\tau-1}$ specifies the i-th component of the vector sequence $\mathbf{x}_{\tau-L}^{\tau-1}$ and C is a constant that only depends on the sequence of observation vectors.

We get the marginal distribution $p(x_{\tau-L+1,i}^\tau, \mathbf{z}_1^\tau)$ by summing (17) over all $\mathbf{x}_{\tau-L+1}^\tau \in \mathbb{X}\backslash i$, where $\backslash i$ means that the sum excludes component i, hence

$$\frac{p(x_{\tau-L+1,i}^\tau, \mathbf{z}_1^\tau)}{C} = \sum_{\mathbf{x}_{\tau-L+1}^\tau \in \mathbb{X}\backslash i} p(\mathbf{z}_\tau \mid \mathbf{x}_\tau) \prod_{j=1}^{N} p(x_{\tau-L+1,j}^\tau, \mathbf{z}_1^{\tau-1}) \,. \tag{18}$$

To compute this marginal distribution we follow the approach of Bahl et al. [8] and introduce the state sequence S_1^{N+1} of the trellis encoder by summing over all possible state sequences. This sum can efficiently be evaluated by the well-known forward/backward recursion. Defining

$$\alpha_{j+1}(s) = \sum_{S_j} \alpha_j(S_j)\, p(z_{\tau,j} \mid S_j, S_{j+1} = s) \cdot \\ \cdot \sum_{x_{\tau,j} \in \mathbb{X}_j} P(S_{j+1} = s \mid S_j, x_{\tau,j})\, p(x_{\tau,j}, \mathbf{z}_1^{\tau-1}) \,, \tag{19}$$

$$\beta_{j-1}(s) = \sum_{S_j} \beta_j(S_j)\, p(z_{\tau,j-1} \mid S_{j-1} = s, S_j) \cdot \\ \cdot \sum_{x_{\tau,j-1} \in \mathbb{X}_j} p(S_{j-1} \mid S_{j-1} = s, x_{\tau,j})\, p(x_{\tau,j}, \mathbf{z}_1^{\tau-1}) \,, \tag{20}$$

we can compute the desired marginal distribution by

$$p(x_{\tau-L+1,i}^\tau, \mathbf{z}_1^\tau)/C = \sum_{S_i, S_{i+1}} \alpha_i(S_i)\, \beta_{i+1}(S_{i+1}) \cdot \\ \cdot\, p(z_{\tau,i} \mid S_i, S_{i+1})\, P(S_{i+1} \mid S_i, x_{\tau,i})\, p(x_{\tau-L+1,i}^\tau, \mathbf{z}_1^{\tau-1}) \,. \tag{21}$$

The boundary conditions, i.e. the values of $\alpha(S_1)$ and $\beta(S_{N+1})$ depend on the termination strategy of the trellis code, e.g. for a terminated code $\alpha_1(0) = \beta_{N+1}(0) = 1$.

Finally, returning to (13) we recognize that $p(x_i^{(\ell)}, \mathbf{z}_1^\tau)$ is the marginal distribution of (21), which can be obtained by summing over all combinations $x_{\tau-L+1,i}^{\tau-1} \in \mathbb{X}_i$ and setting $x_{\tau,i} = x_i^{(\ell)}$.

Now we have all necessary tools complete to state the decoding algorithm:

1) Initialize $p(x_{-L+1,i}^0) = p(x_{1,i}^{L-1}, \mathbf{z}_1^0)\ \forall i$.
2) Use (17) to get $p(x_{\tau-L+1,i}^\tau, \mathbf{z}_1^{\tau-1})$ from $p(x_{\tau-L,i}^{\tau-1}, \mathbf{z}_\tau^{\tau-1})$.
3) Compute marginal distribution $p(x_{\tau,i}, \mathbf{z}_1^{\tau-1})$.
4) Forward/backward recursion according to (19), (20).
5) Compute $p(x_{\tau-L+1,i}^\tau, \mathbf{z}_1^\tau)$ by (21).
6) In (21), replace $p(x_{\tau-L+1,i}^\tau, \mathbf{z}_1^{\tau-1})$ by $p(x_{\tau,i}, \mathbf{z}_1^{\tau-1})$, which yields $p(x_{\tau,i}, \mathbf{z}_1^\tau)$.
7) Compute MS estimates according to (12).
8) Return to 2) and process next received vector $\mathbf{z}_\tau$.

Note that for $L=1$ the distributions $p(x_{\tau-L+1,i}^\tau, \mathbf{z}_1^{\tau-1})$ and $p(x_{\tau,i}, \mathbf{z}_1^{\tau-1})$ coincide and hence steps 3) and 6) can be omitted, which makes this case especially attractive for a practical implementation.

6. SIMULATION RESULTS

For the presented simulations, we model the parameter generation by Gaussian sources $p_{\tilde{u}_i} = p_{\tilde{u}}$ and one-tap ($L=1$) IIR filters $f_i = f$. The filters are designed such that we can

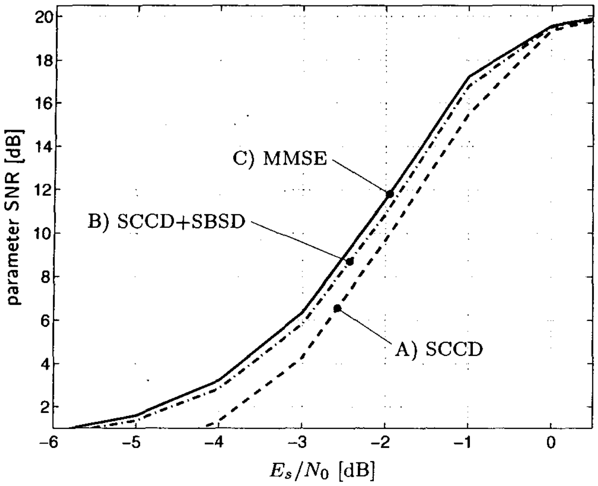

Figure 3: Parameter SNR for uncorrelated source, $\rho = 0$

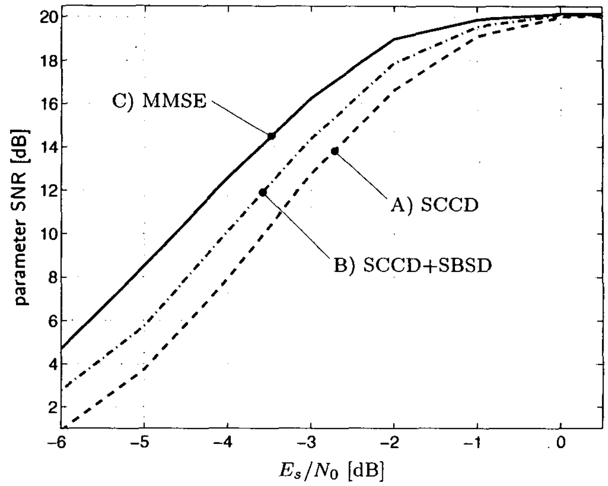

Figure 4: Parameter SNR for correlated source, $\rho = 0.9$

produce parameters u_τ having a well defined correlation $\varphi_{uu}(1) = \rho$ and a normalized output variance $\sigma_u^2 = 1$. We utilize LMQ quantizers with $R_i = R = 16$ levels. The channel code is a rate 1/2 memory $M = 6$ feed forward trellis code with octal generators (133,171).

Three different decoder configurations are considered:

A) SCCD (*Source Controlled Channel Decoding*)
A *Maximum A Posteriori* (MAP) bit-by-bit trellis decoder [8] is used. *A priori* knowledge on bit level is provided by the marginal distribution of recursion (16). The parameter is reconstructed by table lookup.

B) SCCD+SBSD (*Soft Bit Source Decoding*)
Combination of SCCD and MS parameter estimation by SBSD, i.e. *a priori* knowledge is used twice, by channel and source decoding.

C) MMSE (*Minimum Mean Square Error*)
Optimal one step MMSE parameter decoder according to proposed algorithm.

Figures 3 and 4 depict the simulation results for $\rho = 0$ and $\rho = 0.9$, respectively. The SCCD approach in both cases performs worst, but can be enhanced by using SBSD. As expected, the new algorithm is always superior, especially for highly correlated parameters.

7. CONCLUSION

We have developed a new MMSE-optimal decoder for trellis encoded speech parameters. The decoder takes into account the complete observation history and thus is able to exploit the residual time-correlation of the speech parameters. In contrast to *Source Controlled Channel Decoding* (SCCD), which performs *Maximum A Posteriori* (MAP) decision on bit level, the proposed algorithm utilizes *Mean Square* (MS) estimation for parameter reconstruction.

The simulations showed that concatenation of SCCD and *Soft Bit Source Decoding* SBSD enhances the performance of SCCD. They also confirmed the expectation, that the proposed algorithm is superior compared to SCCD even when combined with SBSD. Furthermore, the derivation of the MMSE-decoder proves that for optimal decoding it is sufficient to exploit *a priori* information only once.

REFERENCES

[1] J. Hagenauer, "Source-Controlled Channel Decoding," *IEEE Trans. Communications*, vol. 43, pp. 2449–2457, Sept. 1995.

[2] T. Fingscheidt and P. Vary, "Robust Speech Decoding: A Universal Approach to Bit Error Concealment," in *Proceedings ICASSP*, vol. 3, pp. 1667–1670, Apr. 1997.

[3] C. E. Shannon, "Collected Papers," in *IEEE Press, New York*, p. 40, N. J. A. Sloane and A. Wyner, Eds., 1993.

[4] F. I. Alajaji, N. C. Phambo, and T. E. Fuja, "Channel Codes that Exploit the Residual Redundancy in CELP-Encoded Speech," *IEEE Trans. Speech and Audio Processing*, vol. 4, pp. 325–336, Sept. 1996.

[5] S. Heinen, A. Geiler, and P. Vary, "MAP Channel Decoding by Exploiting Multilevel Source A Priori Knowledge," in *Proceedings European Personal Mobile Communications Conference (EPMCC)*, (Bonn), pp. 467–473, Oct. 1997.

[6] T. Hindelang and A. Ruscitto, "Kanaldecodierung mit A Priori-Wissen bei nicht binären Quellensymbolen," in *ITG-Fachbericht Codierung für Quelle, Kanal und Übertragung*, vol. 146, (Aachen), pp. 163–168, ITG, VDE Verlag, Mar. 1998.

[7] J. Hagenauer and P. Höher, "A Viterbi Algorithm with Soft-Decision Outputs and its Applications," *Proceedings GlobeCom*, pp. 1680–1686, Nov. 1989.

[8] L. Bahl, J. Cocke, F. Jelinek, and J. Raviv, "Optimal Decoding of Linear Codes for Minimizing Symbol Error Rate," *IEEE Trans. Information Theory*, pp. 284–287, Mar. 1974.

[9] S. Heinen, S. Bleck, and P. Vary, "Robust Speech Transmission Over Noisy Channels Employing Non-Linear Block Codes," in *Proceedings Speech Coding Workshop 1999*, (Porvoo, Finland), IEEE, June 1999.

[10] T. Fingscheidt, S. Heinen, and P. Vary, "Joint Speech Codec Parameter and Channel Decoding of Parameter Individual Block Codes (PIBC)," in *Proceedings Speech Coding Workshop 1999*, (Porvoo, Finland), IEEE, June 1999.

[11] S. Heinen, T. Hindelang, and P. Vary, "Channel Codes for Softbit Source Decoding: Estimation of Correlated Parameters," in *3rd ITG Conference Source and Channel Coding*, (Munich), ITG, Jan. 2000.

[12] J. L. Melsa and D. L. Cohn, *Decision and Estimation Theory*. McGraw-Hill Kogakusha, LTD., 1978.