Joint Source Channel Coding and Estimation of Hidden Markov Structures

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Abstract — **We describe techniques for joint source-channel coding of hidden Markov sources using a modified turbo decoding algorithm. This avoids the need to perform any explicit source coding prior to transmission, and instead allows the decoder to utilize the *a priori* structure due to the hidden Markov source. In addition, we present methods that allow the decoder to estimate the parameters of the Markov model. In combination, these techniques allow the decoder to identify, estimate, and exploit the source structure. The estimation does not degrade the performance of the system, i.e. the joint estimation/decoding allows convergence at the same noise levels as a system in which the decoder has perfect *a priori* knowledge of the source parameters. Similar ideas can be successfully applied for the case of hidden Markov channels and combined turbo decoding-equalization for ISI channels.**

I. Introduction

Parallel concatenated codes, or "turbo" codes [1], represent one of the most significant advances in channel coding in recent years. In a turbo encoder, two or more constituent convolutional coders are used, with interleavers used to randomize the relative order of source bits prior to the input the convolutional encoders. The decoder for turbo codes consists of one constituent decoder corresponding to each encoder. The constituent decoders perform iterative processing and exchange of information (called "extrinsic" information in the turbo code literature) about the reliability of the input bits as the decoding progresses.

The usual interpretation of iterative decoding in turbo codes is to consider the extrinsic information at the output of a given constituent decoder as *a priori* information at the input to the next constituent decoder. Memory in the source or channel, however, constitutes an additional source of *a priori* information that can also be utilized during decoding. We show how to modify the decoding process to take advantage of this *a priori* information when the source follows a hidden Markov model and the channel is AWGN. A more detailed explanation of some of the specific modifications can be found in [2].

II. Decoder modifications

To exploit the properties of the hidden Markov model representing the source or the channel, the trellises used in decoding can be replaced with expanded "super-trellises" that jointly describe both the Markov model as well as the convolutional coder. Each one of the branches in the joint super-trellis will have an associated *a priori* transition probability that is a function of the parameters of the hidden Markov model. Each constituent decoder must use the extrinsic information available from the other decoder(s) as well as the *a priori* information (from the Markov model) to obtain a new estimation for the transition probability in each one of its trellis branches. Assuming that the constituent interleavers fully randomize the input bits, we show that the transition probability that each constituent decoder should use in a given branch is the product of the extrinsic probabilities from all the other decoders and the *a priori* probability associated with that branch.

In the description of the decoding modifications we are assuming perfect knowledge of the Markov model parameters. A more powerful approach would allow the receiver to use the noise-corrupted observations to estimate the parameters characterizing the hidden Markov source, and to apply these probabilities in decoding. We introduce a method for performing the estimations jointly with the decoding. Although the underlying idea is the same as in the Baum-Welch algorithm, in contrast with the Baum-Welch algorithm we incorporate the estimation directly into the decoding supertrellises and make use of the soft information available in the decoder.

III. Results

We have simulated a hidden Markov source with parameters $P_t(S_0|S_0) = .1$ and $P_t(S_1|S_1) = .15$, where $P_t(S_k|S_l)$ is the probability of transition from state S_l to S_k and $P_o(0|S_0) = .95$, $P_o(1|S_1) = .925$, with $P_o(i|S_j)$ representing the probability of producing output bit i, $i \in \{0,1\}$, when the source is in state S_j. This hidden Markov source was input to a rate 1/3 encoder that included a systematic bit and two identical recursive 8-state convolutional encoders with generator matrix $G(D) = \frac{1+D+D^2+D^3}{1+D^2+D^3}$ and an interleaver with length 16384. For this source (H=.73 bits/symbol), the theoretical unconstrained limit for E_b/N_0 (considering AWGN chanels) using rate 1/3 codes is approximately -2.2 dB. The modified decoder performs within about 1.2 dB of this limit, showing convergence at $E_b/N_0 = -1.0$ dB (in both cases, when the parameters of the source and the noise in the channel are perfectly known as well as when this information is not available at the beginning of the iterative decoding). A decoder without the modifications described here fails to converge even at an E_b/N_0 of .1 dB. In general, we have observed that the lack of initial knowledge about the source parameters and the noise in the channel does not increase the E_b/N_0 required for convergence. The only negative effect is that more iterations are necessary to achieve convergence.

References

[1] C. Berrou, A. Glavieux, and P. Thitimajshima, "Near Shannon Limit Error-Correcting Coding and Decoding: Turbo Codes," *Proc. of ICC '93*, pp. 1064-1070, 1993.

[2] J. Garcia-Frias and J. Villasenor, "Turbo Decoding of Hidden Markov Sources with Unknown Parameters," *Proc. of DCC '98*, pp. 159-168, March 1998.