Low-complexity serially-concatenated coding for the deep space optical channel

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I. Introduction

NASA is developing optical links to support deep space communication at data rates on the order of 100 Mbit/second. Power efficient signaling is achieved by modulating the data using M-ary pulse-position-modulation (PPM). For certain lasers and detectors, the optimal PPM order is high–$M \geq 256$.

We illustrate performance 0.5–1.0 dB from capacity via the iterative decoding of a serial concatenation of a short constraint length convolutional code and coded PPM through a bit interleaver. To realize the gains of the iterative decoding requires likelihoods to be computed and stored for each PPM symbol. High data rates, large values of M and large interleavers can make the likelihood computation and storage prohibitively expensive.

To reduce the complexity of iterative decoding, we propose to compute and store only a subset of the channel likelihoods. We show that this can be done while suffering a negligible loss in performance. The complexity of implementing the forward-backward algorithm is also reduced when partial likelihoods are retained.

II. Partial Statistics

Suppose only P of each M observations, as well as their indices $\boldsymbol{\mathcal{I}}$, are made available to the receiver. We model the constraint as shown in Figure 1, where $\mathbf{c}, \mathbf{n}, \mathbf{y}$ are codeword, noise and received M-vectors, respectively, ϕ denotes the rule for choosing the P samples, $\phi : \mathbf{y} \rightarrow (\mathbf{y}_{\boldsymbol{\mathcal{I}}}, \boldsymbol{\mathcal{I}})$, $\boldsymbol{\mathcal{I}} \subset \{1, \ldots, M\}, |\boldsymbol{\mathcal{I}}| = P$ and $\mathbf{y}_{\boldsymbol{\mathcal{I}}}$ is the vector of retained samples $\mathbf{y}_i, i \in \boldsymbol{\mathcal{I}}$. The mapping ϕ reduces the dimensionality of the received information, which we expect to severely degrade performance for small P. However, by allowing $\boldsymbol{\mathcal{I}}$ to be a function of the observation $\mathbf{y}$, we will see that the reduction may be implemented with negligible loss.

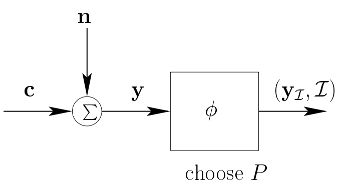

Figure 1: Constrained storage channel model

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The conditional likelihoods

$$p_{\phi(\mathbf{y})|\mathbf{c}}(\phi(y)|c) = p_{\mathbf{y}_{\mathcal{I}}|\mathbf{c}}(y_{\mathcal{I}}|c)p_{\boldsymbol{\mathcal{I}}|\mathbf{c},\mathbf{y}_{\mathcal{I}}}(\mathcal{I}|c, y_{\mathcal{I}})$$

where we explicitly distinguish random variables $\mathbf{y}, \mathbf{c}, \boldsymbol{\mathcal{I}}$ from their realizations $y, c, \mathcal{I}$, are a sufficient statistic for estimation of $\mathbf{c}$ given $\phi(\mathbf{y})$. The term $p_{\mathbf{y}_{\mathcal{I}}|\mathbf{c}}$ is the likelihood that would result if the input were mapped to a P dimensional constellation and the term $p_{\boldsymbol{\mathcal{I}}|\mathbf{c},\mathbf{y}_{\mathcal{I}}}$ is an adjustment to reflect the outcome of the decision.

Figure 2 illustrates performance for a case with $M = 256$, a 4096-bit interleaver, and 8 iterations, on an AWGN channel. We see 0.1 dB degradation when 1/64 of the likelihoods are kept, and negligible degradation when 1/32 are kept.

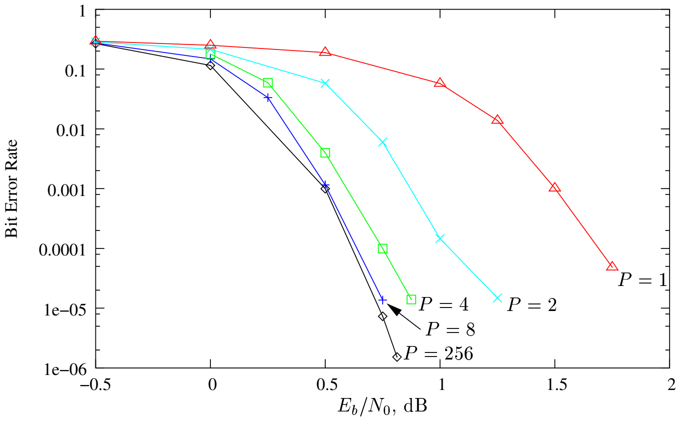

Figure 2: Performance with partial statistics, $M = 256$.

In addition to storing the floating point values, we must save the addresses of the P largest values. This yields

$$\frac{\text{storage for } P \text{ likelihoods}}{\text{storage for } M \text{ likelihoods}} = \frac{P}{M}\left(1 + \frac{\log_2 M}{f}\right),$$

where f is the number of bits used to represent fixed or floating-point values.

III. Partial trellis

With partial statistics, there are only $P+1$ distinct channel likelihoods $p_{\phi(\mathbf{y})|\mathbf{c}}(\phi(y)|c(e))$. One can take advantage of this and use a reduced complexity time-varying trellis. Let $\mathcal{J}_k$ be the collection of parallel edges in the full trellis at time k with the same channel likelihood. Form a *partial* trellis by replacing the edges in $\mathcal{J}_k$ with a single edge with the same initial state and terminal state. Maximum aposteriori decoding may be executed on the partial trellis. The partial trellis will have $|\mathcal{V}|$ states and no more than $|\mathcal{V}|(P + |\mathcal{V}|)$ edges, where $|\mathcal{V}|$ is the number of states on the full trellis.