EXTRACTION OF TIMING ERROR PARAMETERS FROM READBACK WAVEFORMS

Wei Zeng [1], Aleksandar Kavcic [1], Ravi Motwani [2]
[1] DEAS, Harvard University, Cambridge, MA, 02138. [2] Data Storage Institute, Singapore

It is widely accepted that in magnetic recording applications, the detectors/decoders need to be fine-tuned to the signal and noise characteristics in order to achieve maximal gains. Extrapolating these principles to timing recovery loops, we conclude that the most accurate timing recovery loops will be fine-tuned to the timing error statistics of magnetic recording devices. However, state-of-the-art synchronizers typically use standard first or second order timing recovery loops with only 2-3 tunable parameters. Clearly if we can construct an accurate statistical model for the timing error process, we would have the opportunity to fine-tune the timing recovery loop to match the model. In this paper, we propose a Markov model for the timing error, and design two methods (data-aided and non-data-aided) to extract the model parameters from the read-back waveforms. We demonstrate the usefulness of accurate model extraction by comparing a fine-tuned Markov timing recovery loop [1] to the standard Mueller and Muller (M&M) detector [2] with a tuned second order loop filter.

Let T be the bit interval. The timing error ε_k is the difference between the sampling instant of the k-th sample of the readback waveform and the expected sampling instant kT. Since the writing process and the reading process are never perfectly synchronized, the timing error ε_k is a random process. Often this random process is modeled as Gaussian random walk [3]. Though the random walk model is simple, it is often not accurate enough and it does not provide enough parameters to tune the synchronizer. Here, we adopt a tunable model for the timing error process. We quantize the symbol interval into Q levels, and allow ε_k to take values jT/Q, where j is an integer. Obviously, the quantization is an approximation, which, if chosen to be fine enough, introduces only a marginally small quantization error. We refer to the levels jT/Q as the *states* of the timing error process. Next, we assume that the process ε_k is Markov with the probability of transition from state iT/Q to state jT/Q denoted by $q(j|i)=q_{i,\,j}$. Fig. 1 illustrates an example, where non-zero transition probabilities occur only between neighboring states. Obviously, more accurate Markov models with transitions between non-neighboring states are possible (but not considered here). Note that due to the cyclostationarity of the timing error process, $q_{i,\,j}$ must equal $q_{i+Q,\,j+Q}$.

Our modeling task is to observe (capture) a read back waveform (sampled at one sample per symbol interval), and estimate the transition probabilities $q_{i,\,j}$ from the captured samples. Thereby, we assume that the channel impulse (or transition) response is *a priori* known; if it is not known, it can be easily measured. To perform the modeling task, we consider two scenarios: 1) the data-aided scenario where the written bits are known, and 2) the non-data-aided scenario where the written bits are not known and are drawn randomly with a known probability distribution prior to the writing.

The basic tool that we will use for the modeling task is the Baum-Welch algorithm [4]. In its classical from, the algorithm performs the estimation of transition probabilities on a trellis representation of a Markov-memory process. In our case, however, there are two processes with memory: 1) the timing error process, and 2) the channel input process observed through an inter-symbol interference (ISI) channel. Hence, the first task is to build a trellis representation of the joint timing-error/ISI process. The joint timing-error/ISI trellis and the corresponding optimal soft-output detector are given in [5].

In the data-aided scenario, we construct a timing errors trellis that is essentially a subtrellis of the trellis in [5], with Q+2 states, where each state represents the number of samples in a given input symbol interval. A valid path in this timing error trellis corresponds to a possible timing error sequence. The state transition probabilities in this timing error trellis are determined from the parameters $q_{i,\,j}$ of the Markov model shown in Fig. 1. The Baum-Welch algorithm starts with initial guesses of the state transition probabilities $q_{i,j}$, and after each iteration of the algorithm, new estimates of the state transition probabilities are made. For the non-data-aided scenario, a joint trellis [5] should be constructed to represent both the inter-symbol

[1] Wei Zeng, DEAS, Harvard University
33 Oxford St. Cambridge, MA, 02138
617-495-4478, wzeng@deas.harvard.edu

interference and the timing error. Essentially, the difference between the data-aided and the non-data-aided method is in the trellis that is used.

To demonstrate the applicability of the estimation algorithm, in Fig.2 we plot the total squared error between the true and the estimated state transition probabilities as a function of the number of iterations. We notice that the algorithm converges for both the data-aided and non-data-aided scenario, though the knowledge of the training sequence increases the convergence rate, especially at low signal-to-noise ratios. To illustrate the advantage of properly modeling the timing error process, in Fig.3 we compare the bit error rate (BER) resulting from two timing recovery loops. The first is the standard M&M detector with a second order loop filter [2], and the second is the optimal trellis-based timing recovery loop [1] that is fine-tuned to the estimated timing error process. In this comparison, the true underlying timing error process is a random walk whose Gaussian increment has zero mean and standard deviation σ_w, where an aggressive timing error scenario σ_w/T=2% is chosen for illustration purposes. Clearly, the timing loop that is better tuned to the timing error process, gives a lower BER.

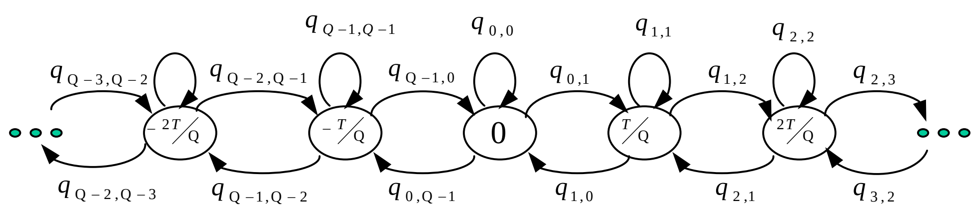

Fig. 1. The random walk model for the timing error process ε_k.

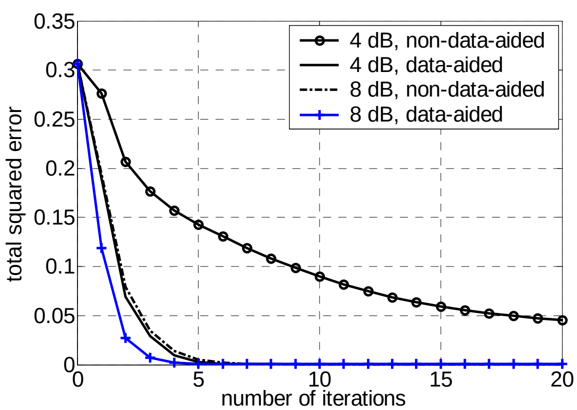

Fig. 2. Total squared error between the true transition probabilities and the estimated transition probabilities.

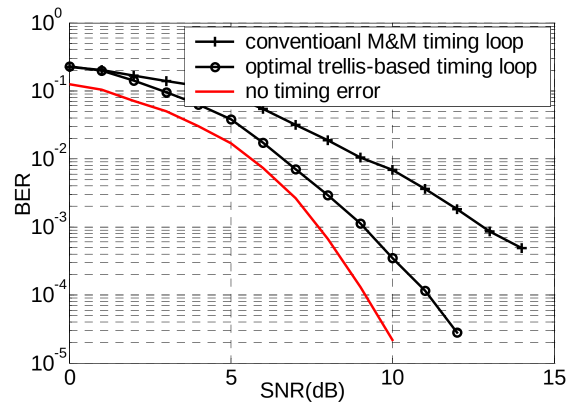

Fig. 3. Bit error rates obtained when using the conventional M&M timing recovery detector with optimized second-order loop filter [2] and the optimal trellis-based timing recovery loop [1].

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