SELF TRAINING FOR PATTERN-DEPENDENT NOISE PREDICTION

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I. INTRODUCTION

Pattern-dependent media noise is already a dominant impairment, and its impact will only grow more severe as areal densities continue to increase. The pattern-dependent noise prediction (PDNP) algorithm [1][2] is an effective strategy for mitigating media noise arising from downtrack transitions, while the recently proposed 2D PDNP algorithm [3] is a 2D extension that jointly mitigates downtrack and crosstrack pattern-dependent noise. In practice such algorithms require accurate estimates of the parameters (including mean offsets, predictor coefficients or matrices, and residual variances or covariance matrices) of the noise model. Traditionally, these parameters are estimated through a training process based on the readback waveforms from a known set of training bits, with the expectation that the noise behavior learned during training will be applicable when later reading back a sector of unknown bits.

We propose a new "training" strategy called self training that eliminates the need for any a priori training. Instead, all parameters can be estimated from scratch, independently from one sector to the next, through an iterative process that iterates between a soft-output channel detector and a channel model estimator. No knowledge of any training bits is required. Importantly, unlike the traditionally trained case (in which a different set of bits on a different part of the disk are used to estimate the parameters), the parameters estimated via self training are based on the same bits, written on the same part of the disk, as those being detected. Numerical results show self training provides a 4% increase in areal density for 1D systems on a set of quasi-micromagnetic simulated channel waveforms.

II. THE SELF TRAINING SCHEME

The self training scheme is shown in Fig. 1. Similar to the expectation maximization (EM) algorithm, the rough idea is to iterate between a PDNP detector (that assumes that the model it receives is accurate) and a model estimator (that assumes the LLR signs are reliable). The hope is that, as iterations progress, the LLR's will grow more reliable, which will in turn result in a better estimate of the model, which will in turn lead to even more reliable LLR's, and so on. As shown in the figure, the readback waveform is first equalized and then fed to a BCJR detector, which produces log-likelihood ratios (LLR's) for the bits. The training proceeds in the traditional way, with two exceptions: the signs of the LLR's are used in place of training bits, and only when all of the LLR's in a block exceed a threshold in magnitude is the data used at all, for in this case the bit decisions are expected to be reliable. The model parameter estimates then produced are then fed back to the detector for the next iteration of the PDNP detector. This process can be iterated for several times if necessary.

III. QUANTITATIVE RESULTS

We test the self training algorithm using a database of quasi-micromagnetic simulated waveforms from Ehime University [4]. The database provides five tracks of readback waveforms which are twice oversampled and perfectly synchronized on different track pitches with bit length of 7.3 nm as well as 25 reader positions and five reader widths. The architecture in Fig. 1 is tested with a MMSE equalizer with 22 coefficients and the central track with 41206 bits is detected. For the first pass, the PDNP parameters are initialized to "zero" so that straight BCJR is executed. We present results for 1D PDNP with a pattern length of 3 bits and two predictor coefficients. Fig. 2 shows the BER after the second iteration of the PDNP BCJR versus threshold used in the second model estimation. The optimal threshold is a tradeoff between the reliable decisions enabled by a large threshold and the quantity of data enabled by a small threshold. A plot of BER versus iteration number is shown in Fig. 3. Interestingly, here we see that the self training algorithm outperforms a genie-aided training (which somehow has perfect knowledge of the bits

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for model estimation purposes only) at the fourth iteration. We plot BER versus track pitch in Fig. 4 after iterations and optimal reader width and position as well as threshold. The results show that self training algorithm gives the same performance of genie-aided training, which is a 4% increase in areal density over a non-PDNP Viterbi detector.

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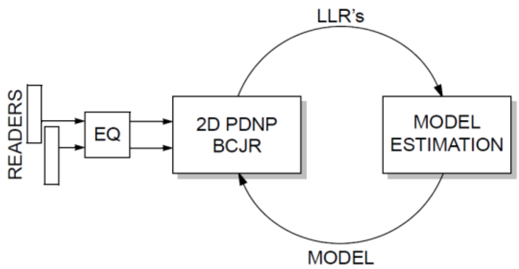

Fig. 1 The self training scheme.

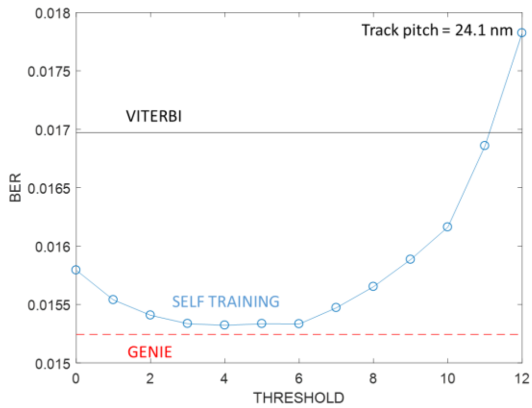

Fig. 2 BER vs. threshold.

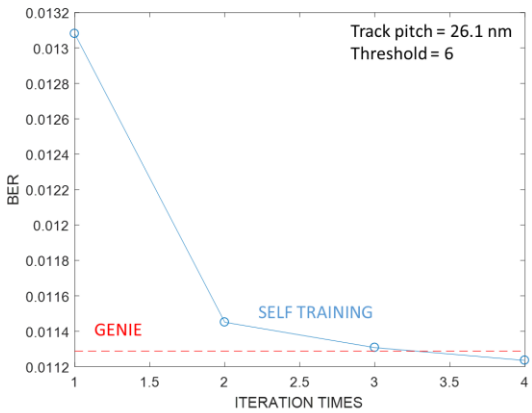

Fig. 3 BER vs. iteration number.

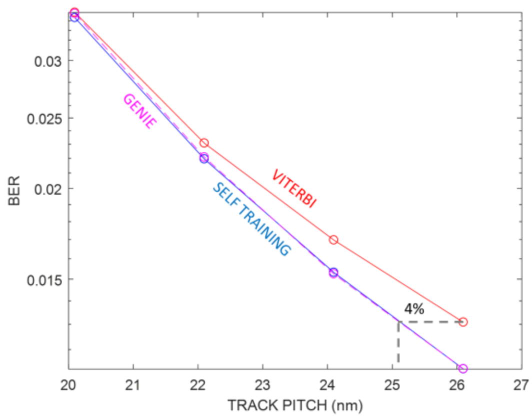

Fig. 4 BER vs. track pitch.