Turbo-detection for Multilayer Magnetic Recording Using Deep Neural Network-based Equalizer and Media Noise Predictor

Amirhossein SAYYAFAN[1], Ahmed ABOUTALEB[1], Benjamin J. BELZER[1], Krishnamoorthy SIVAKUMAR[1], Simon GREAVES[2]

1) Washington State University, Pullman, WA, USA, (a.sayyafan, ahmed.aboutaleb, belzer, siva)@wsu.edu

2) RIEC, Tohoku University, Sendai 980-8577, Japan, simon@riec.tohoku.ac.jp

I. SYSTEM MODEL

In the hard disk drive (HDD) industry, new technologies are being developed to increase density such as two-dimensional magnetic recording (TDMR). TDMR utilizes 2D signal processing without changes to existing magnetic media to get remarkable density gains [1]. In multilayer magnetic recording (MLMR), an additional magnetic media layer is vertically stacked to a TDMR system to achieve additional density gains [2], [3]. We study deep neural network (DNN) based methods for equalization and detection for MLMR, using a realistic grain switching probability (GSP) model [4] for generating waveforms.

Fig. 1 shows a cross-track view of the MLMR system. There are six tracks written at track pitch (TP) 24 nm and bit length (BL) 10 nm on the upper layer. The three tracks are written at TP 48 nm and BL 20 nm on the lower layer. Thus, the system stores four bits on the upper layer for every one bit on the lower layer. To be consistent with [3], we denote the bit sequences written on the upper left and right tracks by $\boldsymbol{a}_{2,L}$ and $\boldsymbol{a}_{2,R}$ respectively, and the bit sequence on the lower track by $\boldsymbol{a}_1$ for the tracks of interest. There are two boundary tracks $\boldsymbol{a}_{b,L}$ and $\boldsymbol{a}_{b,R}$ on the left and right sides of $\boldsymbol{a}_{2,L}$ and $\boldsymbol{a}_{2,R}$, respectively. Readings are obtained at track positions (relative to $\boldsymbol{r}_0$, which is centered on track $\boldsymbol{a}_{b,L}$) of 0, 24, 36, 48, and 72nm, from left to right, and denoted by $\boldsymbol{r}_0$ to $\boldsymbol{r}_5$, respectively.

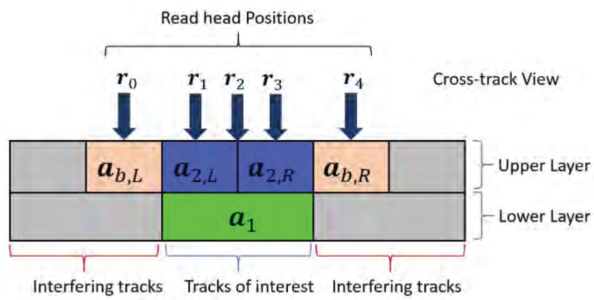

Fig. 1 Cross-track view of the MLMR System

The effective channel model has a media noise term which models signal dependent noise due to, e.g., magnetic grains intersected by bit boundaries. Trellis based detection with pattern dependent noise prediction (PDNP) [5] is standard practice in HDDs. The trellis detector sends soft coded bit estimates to a channel decoder, which outputs user information bit estimates. PDNP uses a relatively simple autoregressive noise model and linear prediction; this model is somewhat restrictive and may not accurately represent the media noise, especially at high storage densities. To address these problems, we design and train DNN based equalizer-separators and media noise predictors. The proposed turbo-detector assumes a channel model for the kth equalizer-separator output $\hat{\mathbf{s}}_k$:

$$\hat{\mathbf{s}}_k = (\mathbf{h}_k * \mathbf{u})(k) + n_m(k) + n_e(k), \tag{1}$$

where $\mathbf{h}_k$ is the partial response (PR) target, $\mathbf{u}$ are the coded bits on the track, $*$ indicates 1D/2D convolution, $n_m(k)$ is media noise, and $n_e(k)$ is reader electronic noise modeled as additive white Gaussian noise (AWGN).

In [3] we proposed a CNN equalizer-separator for MLMR followed by 1D soft output Viterbi Algorithm (SOVA) detectors for all three tracks $\boldsymbol{a}_1$, $\boldsymbol{a}_{2,L}$ and $\boldsymbol{a}_{2,R}$. We proposed BCJR-LDPC-CNN turbo detectors for 1D magnetic recording (1DMR) and TDMR in [6]. This paper combines the equalizer-separator of [3] with a modified version of [6] designed for MLMR.

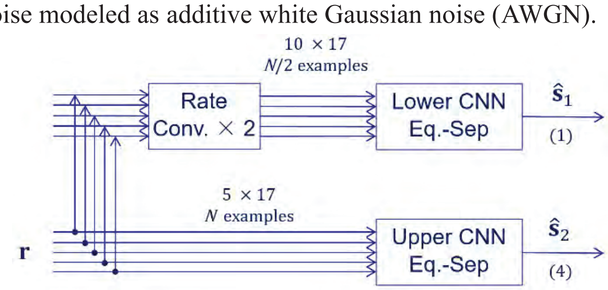

Fig. 2 Architecture of the CNN Equalizer-Separator

II. CNN EQUALIZER-SEPARATOR

We investigate a method for equalization of bit sequences $\boldsymbol{a}_1$, $\boldsymbol{a}_{2,L}$ and $\boldsymbol{a}_{2,R}$ from readings $\boldsymbol{r}_0$ to $\boldsymbol{r}_5$ [3]. Fig. 2 illustrates a convolutional neural network (CNN) equalizer-separator. For the upper layer, the inputs include a sliding window of readings with the size of 5×17. For the lower layer, a rate converter multiplexes the additional readings across-track to have 10×17 input examples, since each reader collects two samples per lower

Benjamin J. BELZER
E-mail: belzer@wsu.edu
tel: +1-509-335-4970
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layer bit, and to maintain a 17-bit down-track footprint. The CNN equalizer iterates with a constrained mean squared error (MSE) solver to adjust the PR target during the training. The lower layer CNN is provided with the reading samples **r** for the five sequences to generate the equalized waveforms $\hat{\mathbf{s}}_1$ for the lower track. The upper layer CNN produces the equalized waveform $\hat{\mathbf{s}}_2$ for the four upper tracks.

III. BCJR-LDPC-CNN TURBO-DETECTOR

Fig. 3 shows the MLMR BCJR-LDPC-CNN turbo-detector. BCJR-LDPC-CNN turbo-detectors for 1DMR and TDMR are employed for the lower and upper layers, respectively. For each layer's turbo-detector, the separate BCJR trellis-based ISI/ITI detector and CNN-based media-noise predictor exchange log-likelihood-ratio (LLR) and media noise estimates to iteratively reduce the BER until convergence. The upper layer's 2D-BCJR detector generates LLR estimates of $\boldsymbol{a}_{2,L}$ and $\boldsymbol{a}_{2,R}$ by performing ISI/ITI equalization on input $\hat{\mathbf{s}}_2$. Since the PR target $\mathbf{h}_2$ is 3×3, the 2D-BCJR state-input window is 2×3, and its trellis has 16 states. The CNN media noise predictor uses the 2D-BCJR LLRs $\mathbf{LLR}_{b_0}$ and $\hat{\mathbf{s}}_2$ to estimate the media noise $\hat{\mathbf{n}}_{m_2}$. The noise $\hat{\mathbf{n}}_{m_2}$ is fed back to the 2D-BCJR to obtain a lower BER. Next, the 2D-BCJR passes LLRs $\mathbf{LLR}_b$ to a low-density parity check (LDPC) decoder. At the end of each turbo-iteration, the decoder generates the final LLRs $\mathbf{LLR}_l$. The lower layer employs a 1D-BCJR with a three-tap PR target $\mathbf{h}_1$ to estimate $\boldsymbol{a}_1$, so its trellis has four states. Areal density (AD) is determined by increasing the LDPC code rate until the decoded BER is $\leq 10^{-5}$. Dotted lines in Fig. 3 indicate optional inner iterations between the BCJR layer detectors.

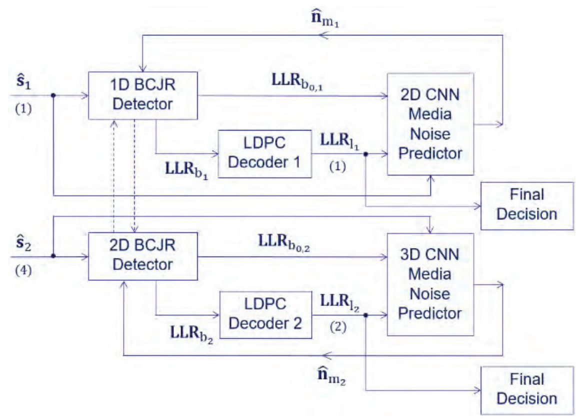

Fig. 3 BCJR-LDPC-CNN turbo-detector for MLMR system

Table I Simulation results for MLMR

Method/ Layer	Detector BER	AD (Tb/in^2)	Code Rate
Reference	0.0146	2.2102	0.8222
Upper	0.0485	1.9640	0.7306
Lower	0.0274	0.5507	0.8195

IV. RESULTS AND DISCUSSION

Table I presents simulation results for the proposed turbo-detectors for MLMR on the GSP model [4]. Each block contains 82,412 bits per track on the upper layer and 41,206 bits per track on the lower layer. For the CNN equalizer-separator and BCJR-LDPC-CNN detector, we use 59, 1, and 20 blocks as the training, validation and test datasets respectivly. The average BERs before the LDPC decoder are shown in Table I. As a reference, we evaluate a one-layer TDMR system (without lower layer interference) with TP 24 nm and BL 10 nm using the upper layer's BCJR-LDPC-CNN architecture. The maximum code rate achieved by the reference system is 0.8222. In comparison, for the MLMR system, the maximum code rates are 0.7306 and 0.8195 on the upper and lower layers, respectively. Since there are four bits on the upper layer per one bit on the lower layer, the total rate of the MLMR system is 0.7306 + 0.8195/4 = 0.9354. *Thus, the areal density gain of the MLMR system over the TDMR system is (0.9354 – 0.08222)/ 0.8222 = 13.77%.* The conventional baseline comparison involving a linear equalizer followed by 1D-PDNP will be reported in an expanded version of this paper.

REFERENCES

[1] K. S. Chan, R. Radhakrishnan, K. Eason, M. R. Elidrissi, J. J. Miles, B. Vasic, and A. R. Krishnan, "Channel models and detectors for two-dimensional magnetic recording," *IEEE Trans. Mag.*, vol. 46, no. 3, pp. 804–811, March 2010.

[2] K. S. Chan, A. Aboutaleb, K. Sivakumar, B. Belzer, R. Wood and S. Rahardja, "Data Recovery for Multilayer Magnetic Recording," *IEEE Trans. Mag*., vol. 55, no. 12, pp. 1-16, Dec. 2019.

[3] A. Aboutaleb, A. Sayyafan, K. Sivakumar, B. J. Belzer, S. Greaves, K. S. Chan, and R. Wood, "Deep Neural Network-based Detection and Partial Response Equalization for Multilayer Magnetic Recording," *IEEE Trans. Mag*., vol. 57, no. 3, pp. 1-12, March 2021.

[4] S. Greaves, K. S. Chan, and Y. Kanai "Areal Density Capability of Dual-Structure Media for Microwave-Assisted Magnetic Recording," *IEEE Trans. Mag*., vol. 55, no. 12, pp. 1-9, Dec. 2019.

[5] J. Moon and J. Park, "Pattern-dependent noise prediction in signal dependent noise," *IEEE Jour. Sel. Areas Commun.*, vol. 19, no. 4, pp. 730–743, Apr 2001.

[6] A. Sayyafan, A. Aboutaleb, B. J. Belzer, K. Sivakumar, A. Aguilar, C. A. Pinkham, K. S. Chan, and A. James, "Deep Neural Network Media Noise Predictor Turbo-detection System for 1-D and 2-D Dimensional High-Density Magnetic Recording," *IEEE Trans. Mag*., vol. 57, no. 3, pp. 1-13, March 2021.