Deep Neural Network-based Detection and Partial Response Equalization for Multilayer Magnetic Recording

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I. INTRODUCTION

The hard disk drive (HDD) industry stores data at areal densities close to the capacity limit of the one-dimensional (1D) magnetic recording channel [1]. New technologies are emerging to increase density, including heat assisted magnetic recording (HAMR), microwave-assisted magnetic recording (MAMR), and two-dimensional magnetic recording (TDMR). TDMR employs 2D signal processing to achieve significant density gains, without changes to existing magnetic media. Recent encouraging studies [2]-[5] propose multilayer magnetic recording (MLMR): vertical stacking of an additional magnetic media layer to a TDMR system to achieve further density gains. Using a realistic grain flipping probability (GFP) model to generate waveforms [3], [4], we investigate the design of deep neural network (DNN) based methods for equalization and detection for MLMR.

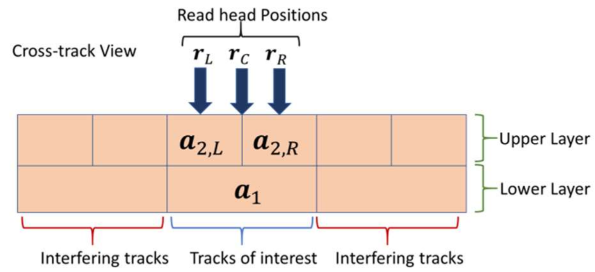

Figure 1: Cross-track View of the MLMR System.

Fig. 1 shows a cross-track view of the MLMR system considered. On the upper layer, six tracks are written at track pitch (TP) 48 nm and bit length (BL) 11 nm. On the lower layer, three tracks are written at TP 96 nm and BL 22 nm. Hence, the system stores one bit on the lower layer for every four bits on the upper layer. Consistent with the notation in [5], the lower layer is indexed by 1, and the upper layer by 2. For the tracks of interest, 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 $\boldsymbol{a}_1$. Readings are obtained every 11 nm down-track at the left, center, and right cross-track positions, and measured reading sequences are denoted by $\boldsymbol{r}_L, \boldsymbol{r}_C$, and $\boldsymbol{r}_R$, respectively.

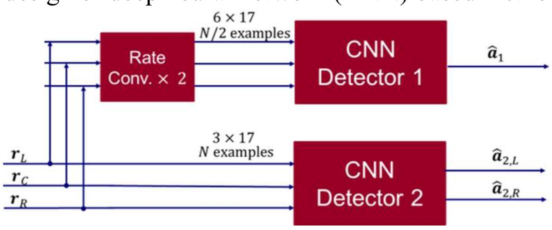

Figure 2: Architecture of the CNN Detector System.

We compare three methods for detection and equalization of bit sequences $\boldsymbol{a}_1, \boldsymbol{a}_{2,L}$, and $\boldsymbol{a}_{2,R}$ from readings $\boldsymbol{r}_L, \boldsymbol{r}_C$, and $\boldsymbol{r}_R$. The first method relies only on convolutional DNNs (CNNs) to detect the bit sequences. Fig. 2 illustrates the CNN-only system, which consists of CNNs for detection on each layer. Readings within a 3×17 sliding window comprise input examples for the upper layer bits. Since each reader collects two samples per lower layer bit, and to maintain a 17-bit down-track footprint, a rate converter multiplexes these additional readings across-track, resulting in size 6×17 lower layer input examples. Each CNN detector accepts input examples and estimates its corresponding bit label. The second method consists of a non-linear CNN equalizer followed by a Viterbi Algorithm (VA) for detection and is illustrated in Fig. 3. During training, the CNN equalizer iterates with a constrained mean squared error (MSE) solver to adjust the target partial response (PR) masks. The third method is the conventional 2D-linear equalizer followed by a VA. The 2D-linear equalizer also iterates with a constrained MSE solver to adapt the target masks. We use the VA in [5], which is the ML detector for an ideal MLMR channel that does not incorporate erasures caused by the write process.

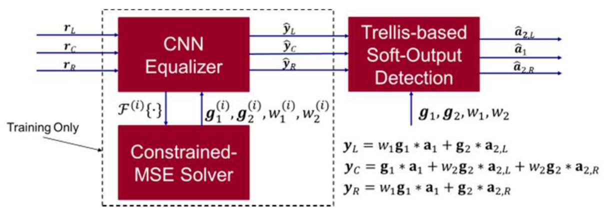

Figure 3: Architecture of the CNN Equalizer-VA. System.

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Work funded by NSF grant CCF-1817083

Figures 4 and 5 detail the architectures equalizer and detector CNNs, respectively. The equalizer CNN minimizes the MSE between its output and the ideal PR waveforms $\boldsymbol{y}_L, \boldsymbol{y}_C$, and $\boldsymbol{y}_R$ in Fig. 3. The detector CNN minimizes the cross-entropy loss function between the correct bit labels and its soft-output estimate. Stochastic gradient descent is used to update the weights in both networks. The detection CNN includes residual paths, which enable it to achieve higher accuracies than equal depth CNNs without residual paths [6]. Since the detection CNN implicitly equalizes and then detects bit sequences, it benefits from increased depth, and, hence, from incorporating residual paths. In contrast, since the equalizer CNN is followed by a VA, we have found that the equalizer CNN does not require increased depth to perform well.

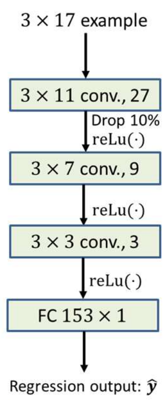

Figure 4: CNN Equalizer

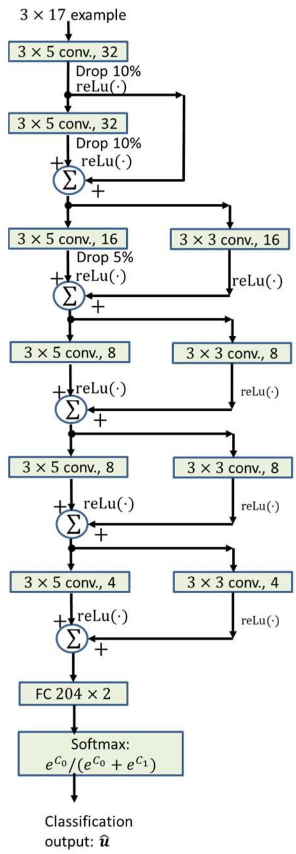

Figure 5: CNN Detector Architecture

II. RESULTS AND DISCUSSION

We trained the three methods mentioned on 60 blocks of waveforms generated based on the GFP model [3]. Each block contains 82,412 bits per track on the upper layer and 41,206 bits per track on the lower layer. Table 1 summarizes the detection BERs obtained during testing for the three methods studied. The testing dataset consists of 20 blocks. As a reference, we evaluated the BER for a one-layer TDMR system with TP 48 nm and BL 11 nm. The detection BER achieved by a CNN detector for this one-layer system is 0.0563. Following the CNN detector, we interfaced a channel decoder that performs coset-decoding using appropriate code rates. We then adjusted the rates via code design and puncturing so that the decoder BER is less than 10^{-5}. This results in a maximum code rate of 0.7477 achieved by the one-layer TDMR system. In comparison, the maximum code rates achieved by the two-layer MLMR system are 0.7116 and 0.6289 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 $0.7116 + 0.6289/4 = 0.8688$. Hence, the areal density gain of the MLMR system over the TDMR system is $(0.8688 - 0.7477)/0.7477 = 16.20\%$.

Table 1: BER comparison. One-layer system BER is 0.0563.

Method / Layer	2D-Linear MMSE-VA	DNN Detector	DNN Equalizer – VA
Upper	0.1335	0.06610	0.06733
Lower	0.1812	0.1020	0.1190

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