Turbo-Connected Neural Network Media Noise Cancellation Strategy for Asynchronous Multitrack Detection

Elnaz Banan Sadeghian[1], *Member, IEEE*
[1]Department of ECE, Stevens Institute of Technology, Hoboken, NJ 07030, USA, ebsadegh@stevens.edu

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Multitrack detection architectures provide throughput and areal density gains over the current industry's standard of single-track detection architectures. One major challenge of multitrack architectures is the complexity of implementing conventional pattern-dependent media noise prediction (PDNP) strategy within the multitrack symbol detector. In this paper we propose a neural network media noise predictor with manageable complexity that iterates with our rotating target (ROTAR) symbol detector in the turbo equalization fashion to predict and cancel the media noise for multitrack detection of asynchronous tracks. We evaluate the proposed detection strategy on a realistic two-dimensional magnetic-recording channel, and find that the proposed solution can effectively mitigate the media noise and therefore can replace the prohibitively complex PDNP solution for multitrack detection.

***Index Terms*—Intertrack interference, multitrack detection, multiple-input multiple-output (MIMO) channel, timing recovery, turbo equalization, two-dimensional magnetic recording (TDMR).**

I. Introduction

The standard media noise mitigation technique is the pattern-dependent noise prediction algorithm [1]–[3]. This algorithm adds a linear predictor to the trellis-based symbol detector. The additional taps of the noise predictor filter exponentially increase the number of the trellis states. Consequently, the complexity of the resulted detector will be $2^{K(\ell+\Delta)}$, where K is the number of tracks to be jointly detected, ℓ is the length of the target response, and Δ is the length of the noise predictor filter. Although this added complexity is hesitantly tolerated in current industry's single-track read channels where $K = 1$, when we move to the multitrack detection where K can potentially be 2, 3, or more, the conventional PDNP leads to a state explosion of the trellis-based detector and can no longer be implemented. Further, our ROTAR detector of [4]–[6], in order to account for the asynchrony of the tracks being detected, also adds a minimum of $2 \times (K-1)$ additional memory elements to the target response. This means that if the conventional PDNP is to be implemented within ROTAR, the number of trellis states will grow to a formidable $2^{K(\ell+\Delta)+2\times(K-1)}$. Therefore, a straightforward extension of the conventional PDNP to a multitrack trellis-based symbol detector and especially ROTAR is not possible.

In addition, the conventional PDNP mentioned above only considers the noise in the downtrack dimension and ignores it in the crosstrack dimension. A 2-D extension of the traditional 1-D PDNP is proposed in [7], however, with the above mentioned added complexity and for multitrack detection of *synchronous tracks*. In this paper we develop such a strategy for multitrack detection of the more realistic *asynchronous tracks* with *manageable complexity* within the GPRML read channel of [6]. The idea is to remodel the outputs of our asynchronous partial-response (APR) equalizer [6] such that both the signal part and the noise part of the outputs are functions of the bits written on multiple adjacent tracks, according to

$$\mathbf{y}_k = \mathbf{s}(\mathbf{A}_k) + \mathbf{n}_k(\mathbf{A}_k), \tag{1}$$

where $\mathbf{y}_k$ is the vector of the equalized readback samples at time k, and both the signal $\mathbf{s}$ and the zero-mean noise $\mathbf{n}$ depend on the matrix-valued pattern $\mathbf{A}_k = [\mathbf{a}_{k+I}, ..., \mathbf{a}_k, ..., \mathbf{a}_{k-J}]$, where $\mathbf{a}_k$ contains the fractionally delayed bits on the adjacent tracks of interest at time k. Since the characteristics of the media noise depend on the pattern of the written bits, we model the noise as a pattern-dependent autoregressive Gaussian process with memory N_p, according to

$$\mathbf{n}_k = \sum_{i=0}^{N_p} \mathbf{P}_i(\mathbf{A}_k)\mathbf{n}_{k-i} + \mathbf{\Lambda}(\mathbf{A}_k)\mathbf{u}_k, \tag{2}$$

where $\mathbf{u}_k \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ is a matrix-valued white sequence of Gaussian noise vectors, $\mathbf{\Lambda}(\mathbf{A}_k)$ is a pattern-dependent standard deviation matrix, and where $\{\mathbf{P}_i(\mathbf{A}_k)\}$ are the pattern-dependent autoregressive filter coefficients.

A main approach, therefore, is to, upon observing $\{\mathbf{y}_k\}$, find a joint ML solution for the signal and the noise parts in the above multitrack detection problem in the face of pattern-dependent noise. The Viterbi algorithm provides this solution, that is a solution for detecting the state sequence of a finite-state machine based on observations of the APR equalizer outputs contaminated by the media noise. Such solution, however, requires complete knowledge of the autoregressive filter coefficients $\{\mathbf{P}_i(\mathbf{A}_k)\}$, the pattern-dependent standard deviation matrices $\{\mathbf{\Lambda}(\mathbf{A}_k)\}$, and the pattern-dependent signal components $\{\mathbf{s}(\mathbf{A}_k)\}$. Normally, the PDNP mechanism estimates these parameters during training where bits are known and results in a trellis where each bit pattern (each trellis branch) has its own set of parameters and thereby its own predicted noise pattern. This entire process of adding noise predictors to the trellis yields $2^{K(N_p+I+J)}$ states, where $I+J$ and N_p can be viewed as the length of the target response and the noise predictor filter, respectively. Also, if we add the ROTAR mechanism to mitigate the asynchrony, we yield the total of $2^{K(N_p+I+J)+2\times(K-1)}$ states which is impractical.

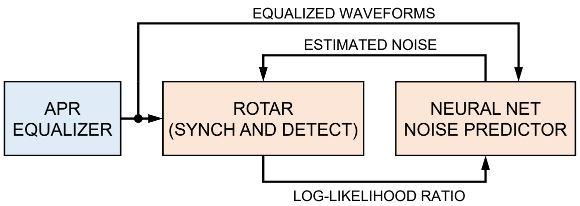

Fig. 1. Block diagram of the ROTAR-NN noise predictor turbo detector.

II. Turbo-Connected Neural Network Noise Predictor and ROTAR Detector

Our proposed approach to the joint estimation of the signal and the noise in (1) is to iteratively adapt between a solution for the signal and a solution for the noise. This approach follows the well-established turbo equalization (also known as the turbo detection) principle in communication systems [8]. Thereby, the idea is to avoid the state explosion due to the PDNP mechanism by separating the symbol detection and media noise prediction into two separate modules and then use the turbo equalization principle to exchange information between them. Further, since a neural network can better learn and therefore predict the nonlinear characteristics of the media noise, we use a neural network in place of the conventional autoregressive model of (2). This idea has been explored for the 1-D magnetic recording case where a single-track of interest is detected from a single readback waveform [9].

Fig. 1 shows our proposed strategy for predicting the media noise using a neural network within our GPRML read channel for multitrack detection of asynchronous tracks. The soft output extrinsic information is passed from ROTAR to the noise predictor which in return provides an estimate of the noise to be subtracted form the branch metrics within the ROTAR algorithm. The equalized outputs are also fed to the noise predictor network. We explored using a multilayer perceptron of four layers and a deep neural network and observed efficient performance with the multilayer perceptron.

III. Simulation Results

The simulations are performed on a data set provided by data storage institute [10]. The waveforms are generated from the grain-flipping probability model in building the magnetized medium. This model generates realistic 2-D waveforms with media noise. A write frequency offset of $\tau_k^{(2)} = k\Delta T_2/T = 2 \times 10^{-4}k$, where $1/T$ is the ADC sampling rate, is injected into the bits of TRACK 2 by linearly shifting the position of the writer. The rest of the tracks are written without any timing offsets. Fig. 2 shows the BER performance of the ultimate proposed read channel of Fig. 1 in comparison with the same GPRML read channel that lacks the noise cancellation mechanism. The figure plots the average BER performance for the two middle tracks being detected using two readers separated based on track pitch (width) (TP). The proposed read channel is trained anew for each reader spacing to find the optimum target and equalizer pair, and the neural network weights for different readback waveforms selected.

The curve labeled "GPRML, W/ NN NOISE CANCELLATION" is the performance of the proposed read channel where the neural network noise predictor has four fully connected hidden layers that apply tangent-sigmoid activation

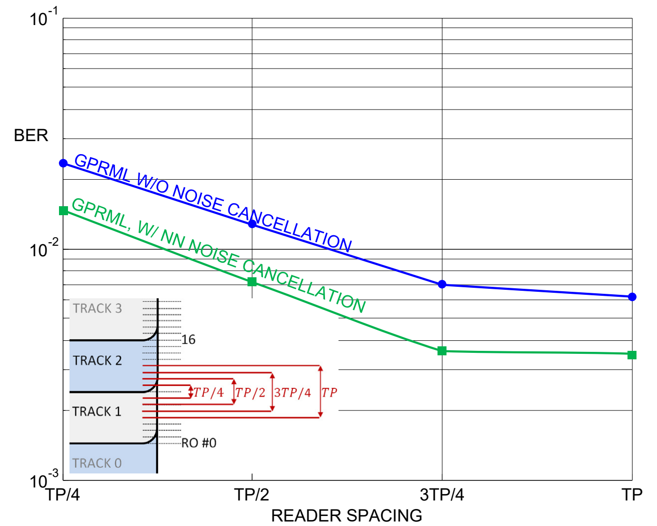

Fig. 2. BER performance of the proposed read channel with and the same read channel without the neural network noise cancellation.

function to their inputs. The baseline read channel is the same as the proposed read channel without any noise cancellation mechanism and is labeled as "GPRML, W/O NOISE CANCELLATION". Since the prediction functionality is not integrated into the trellis of ROTAR, the complexity of the trellis remains equal to the complexity of only the ROTAR detector without noise cancellation, that is $2^{K\times\ell+2\times(K-1)} = 2^{2\times1+2\times1} = 16$ states. This is in contrast to adding the standard PDNP mechanism into ROTAR which would have resulted in $2^{K(N_p+I+J)+2\times(K-1)} = 2^{2(8+1)+2\times1} = 1048576$ states. The proposed read channel shows an average 43.75% reduction in BER, and an average 55% gain in the areal density compared to the baseline read channel without any noise cancellation mechanism.

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