Iterative Decoders Robust to Threshold Voltage Uncertainty

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***Abstract*—In this presentation, we provide an analysis of the sensitivity of finite-alphabet iterative decoders (FAID) for low-density parity check (LDPC) codes to a threshold/reference voltage uncertainty in Flash memory channels. We show that optimizing the FAID message update function makes a decoder tolerant to the log-likelihood ratio quantization-threshold mismatch, and improves greatly the robustness of the decoder compared to the classical Min-Sum decoder.**

I. Introduction

Finite alphabet iterative decoding (FAID) for low-density parity check (LDPC) codes offers desired error performance in both waterfall and error-floor regions while permitting low hardware complexity and high decoding speed [1], [2]. In [3], we presented a field-programmable gate array (FPGA)-based FAID architecture for Flash memories which outperforms the existing hardware solutions known in the literature. However, the error statistics and the Flash channel parameters vary widely, and depend not only on the flash memory technology and underlaying process variability, noise sources and cell-to-cell interference but also on the data-page organization and on how the program, erase and sensing processes are handled by a controller. For example in a triple-level cell (TLC) Flash memories, the most/center/least significant bits ((M/C/L)SB) have different raw bit error rates (RBERs) and depend on voltage level labeling [4]. Optimal target threshold voltage levels that represent three-bit symbols are achieved by sophisticated cell programming techniques, but since in NAND Flash memories with smaller feature size only a small number of electrons in the floating gate distinguishes neighboring symbols levels, these threshold voltages are random variables with variances that increase with the decrease of the feature size. Due the channel model (or experimental data) inaccuracy as well as due to the variability among devices, the threshold and reference voltages (quantization levels) fluctuate from their optimal levels [5]. This affects the accuracy of the channel bit outputs and soft-information (log likelihood ratios (LLRs)) presented to an iterative decoder, and affects the decoding frame error rate (FER) performance. Several studies have demonstrated a significant impact of LLR inaccuracy to Belief Propagation decoding algorithm and its derivatives such as Min-Sum decoders (see for example [6]).

In this presentation, we provide an analysis of the sensitivity of FAID to threshold/reference voltage mismatch. We show that the flexibility in choosing a message update function of FAID, allows us to design decoders that are tolerant to the quantization partition level mismatch.

II. Model for mismatched Thresholding

In current TLC memory chips, the three bits stored in a single cell are mapped into three different pages, and the bits in different pages are encoded, read and decoded independently, thus we model the storage of individual bits as transmission through a binary-input, quantized-output additive noise channel. We focus in this presentation to the case when the soft information provided to the LDPC decoder is limited to 2 soft-bits. We thereby assume that only one soft-read is performed in addition to the hard-read of the flash memory, which implies that two quantization thresholds (QTs) are necessary. The hard-read threshold is assumed to be correctly estimated through a read-retry process, while the soft-read threshold T may be wrongly estimated. This model does not capture all defects that can appear in the NAND device, such as programming errors. Such defects will be analyzed in a future publication.

The channel output u is compared with the quantization thresholds (QTs) $\{-T, 0, T\}$, and quantized to the four channel output log-likelihood ratio (LLR) levels denoted as $-C_2$, $-C_1$, $+C_1$ and $+C_2$, resulting in a binary-input quaternary-output channel with transition probabilities β_2, β_1, α_1 and α_2. For this channel, the probability of error (corresponding to the RBER) is equal to $\alpha = \alpha_1 + \alpha_2$. The optimal soft-read threshold T is obtained by maximization of the mutual information (MI) between quantized channel input and output. The actual, suboptimal soft threshold $\tilde{T}$ used for LLR quantization is assumed to perturbed by a random shift δ, distributed as a zero-mean Gaussian RV with variance σ_δ^2, as shown on Fig. 1.

$$\tilde{T} = T + \delta, \quad \delta \sim \mathcal{N}(0, \sigma_\delta^2). \tag{1}$$

We assume that the same $\tilde{T}$ is used for quantization of the likelihoods across the entire codeword. Furthermore, we assume that the bits of a codeword are stored physically close to each other in the TLC memory and experience the same QT mismatch δ, i.e., the channel is block stationary in this sense. For mathematical convenience we also assume that the voltage amplitude is fixed and that the soft thresholds $-\tilde{T}$ and $\tilde{T}$ are random – it is straightforward to see that this is equivalent to having fixed QTs and varying threshold voltages.

III. Robust FAID optimization

A FAID is typically derived by optimizing the variable node update rule for good performance both in the waterfall and the error floor region, assuming a perfect estimation of the quantization threshold T [1]. Clearly, the mismatch δ

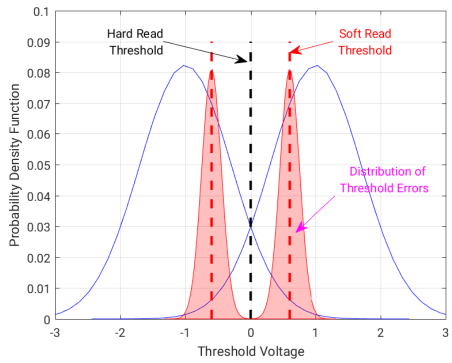

Fig. 1. Error Model on the Quantization Threshold

affects this decoder design process, and consequently a good decoder derived for the case when there is no QT mismatch is not necessarily robust. The QT errors affect both waterfall and error-floor, but in this presentation we focus on waterfall region, while error floor is left for future research. As a first illustration, we have drawn in Fig. 2 the FER curves of the 3-bit offset corrected Min-Sum and a FAID optimized with the correct QT, T. The simulations have been performed with the exact T, and with its mismatched version $\tilde{T}$ for different variances σ_δ^2. A QC-LDPC code with rate $R = 0.89$ and codeword length $N = 2$KBytes is used. Due to the randomness of QTs, there is an inherent channel capacity loss compared to the channel with optimal QTs, which results in the waterfall performance loss. For example, for a fixed $\delta = 0.2$, the capacity loss is approximately 0.01, which translates into the RBER loss of 0.001 or SNR loss of 0.25 dB. We can see on figure 2 that this loss impacts both the Min-Sum and the non-robust FAID decoder.

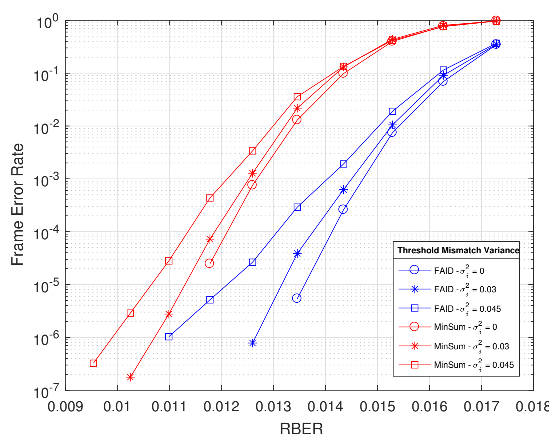

Fig. 2. Performance of MinSum and FAID decoders to threshold mismatch

We now present a methodology for designing FAID decoders robust to threshold mismatch, based on the concept of decoding diversity [2]. Instead of looking for a single FAID update rule for the optimal QT T, we separately optimize FAIDs for the mismatched values $T - \delta$ and $T + \delta$, for a fixed δ, and obtain two decoding rules: $\mathcal{D}_{-\delta}$ and $\mathcal{D}_{+\delta}$. The objective of this strategy is to obtain one decoding rule which is good only for the left-shift mismatch, and another decoding rule which is good only for the right-shift mismatch, such that when combined together, the iterative decoder is robust to the noise model 1. The decoders $\mathcal{D}_{-\delta}$ and $\mathcal{D}_{+\delta}$ are run in a sequential diversity fashion [2], and decoder $\mathcal{D}_{+\delta}$ is triggered only when $\mathcal{D}_{-\delta}$ fails to converge to a valid codeword. Fig. 3 shows the performance of this strategy for the same simulation settings as in Fig. 2. We can see that this combination of two FAIDs is much more robust to the QT variation than the stand alone decoders of Fig. 2.

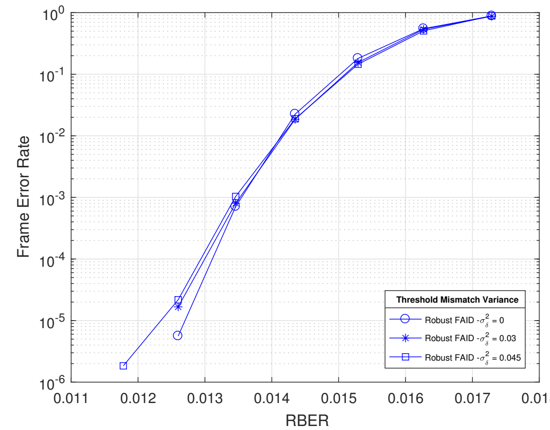

Fig. 3. Robustness of FAID decoder diversity to threshold mismatch

IV. Conclusion

In this presentation, we confirmed that classical iterative decoders are sensitive to threshold voltage uncertainty in quantized NAND flash channels. We also showed that due to the ability of FAID decoders to adapt to the channel conditions, and due to their ability to operate in the decoder diversity mode, they provide an iterative decoding solution that is more robust to LLR quantization threshold mismatches.

Acknowledgments

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