A Study on the Fitness of GA for Improving SP Decoding Performance

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We study low-density parity-check (LDPC) coding and iterative decoding methods for shingled magnetic recording (SMR) in ultra-high-density hard disk drives (HDDs). Previously, we applied a neural network to evaluate the log-likelihood ratios (LLRs) related to row operations in the sum-product (SP) decoder for LDPC code. Then, we updated the LLR considering the influence of noise depending on the recording pattern by providing the LLRs for the decoding target and its adjacent bits to the neural network in SP decoding. Furthermore, we explored the optimal parameters to update the LLRs by applying the genetic algorithm (GA). In this study, to explore more optimal update parameters, we propose the fitness to enhance the accuracy of selecting the LLR to be updated and the number of update targets. Then, we aim to improve the performance of SP decoding based on the GA results. As a result, applying the proposed fitness to GA remains in high selection accuracy and increases the number of updating targets in SP decoding. Also, it achieves error-free performance with fewer iterations of turbo equalization compared to the conventional fitness.

***Index Terms*— Genetic algorithm (GA), low-density parity-check (LDPC) code, neural network, shingled magnetic recording (SMR), sum-product (SP) decoding.**

I. Introduction

In recent years, the explosive increase in data volume has required even higher-density hard disk drives (HDDs). Therefore, we are focusing on the shingled magnetic recording (SMR) [1], which enhances perpendicular magnetic recording (PMR), and developing signal processing methods. We studied the performance improvement of low-density parity-check (LDPC) coding and iterative decoding methods in SMR [2]. In the SMR, due to narrow tracks, signal processing methods are required to reduce the influence of inter-track interference (ITI) and signal-dependent noise like transition jitter. We have achieved the reduction of the effects of ITI by applying a two-dimensional finite impulse response (TD-FIR) filter [3]. Also, to consider the influence of signal-dependent noise, we proposed the sum-product (SP) decoder in which a neural network evaluates the log-likelihood ratio (LLR) related to row operations using the LLRs of the decoding target bit and its adjacent bits and updates the LLR based on the neural network outputs [4]. Furthermore, we showed that a genetic algorithm (GA) is useful to explore updating parameters such as the thresholds and weights in the neural network.

In this study, to explore more optimal update parameters, we propose the fitness to enhance the selection accuracy of the LLR to be updated and the number of update targets. Then, we aim to improve the performance of SP decoding based on the GA results.

II. Read/Write System

Figure 1 shows the block diagram of the SMR read/write (R/W) system with the LDPC coding and iterative decoding. The system assumes the areal recording density of 4 Tbit/inch^2. The R/W consists of the granular media and heads with R/W sensitivity function shown in [5]. In addition, the system noise defined by signal-to-noise ratio (SNR) is added at the reading point as assuming the electrical noise due to the head amplifier and read head, and is defined by $\mathrm{SNR}_S = 20\log_{10}(A/\sigma_s)$ [dB],

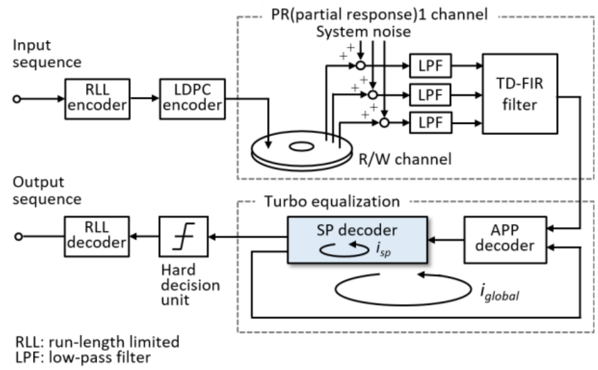

Fig. 1 The block diagram of SMR R/W system with the LDPC coding and iterative decoding.

where A is the positive saturation level of the waveform reproduced from an isolated magnetic transition and σ_s is the root-mean-square (RMS) value of the system noise in the bandwidth of the the channel bit rate f_c. The turbo equalization works between an a posteriori probability (APP) decoder and an SP decoder iteratively, where i_{sp} stands for the maximum number of iterations in the SP decoder, and i_{global} stands for the turbo equalization. Then, the bit error rate (BER) is obtained by comparing the input sequence with the output sequence.

III. Simplification of neural network by HGA

The SP decoding performs based on a parity check matrix and consists of row operations, parity checks, iterative decoding checks, column operations, extrinsic value operations, and posterior value operations. In this study, we employ an LDPC code defined by the parity check matrix with a code length of 4,096 bytes, a column weight of 3, and a row weight of 30, so the SP decoder calculates 3 LLR sequences. Similar to [4], we focus on $\ln \gamma_k^n$, the LLR related to the row operation. γ_k^n denotes the transition probability from the previous point to the current point on the trellis diagram [6]. Figure 2 shows the relationship between the parity check matrix and the neural network configuration. Here, for simplicity, a case is illustrated in which the code length is 12, the column weight is 3, and the

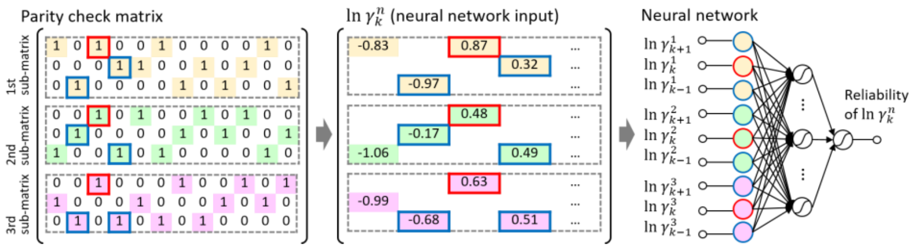

Fig. 2 Relationship between the parity check matrix and the neural network configuration.

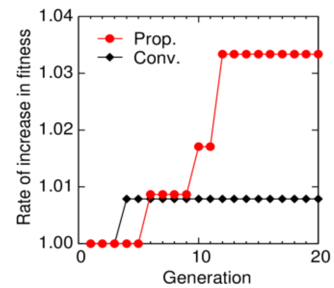

Fig. 3 Rate of increase in fitness.

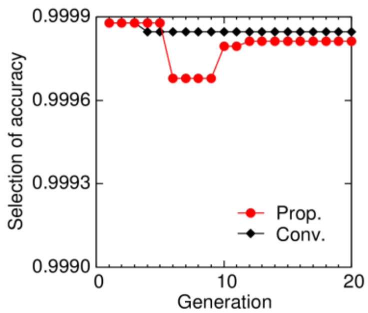

Fig. 4 Selection accuracy of the LLR to be updated.

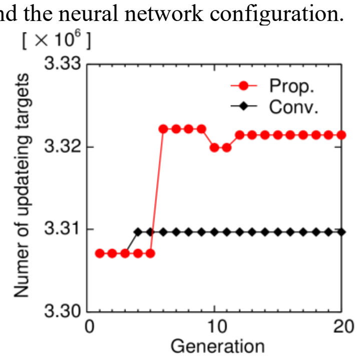

Fig. 5 Number of updating targets.

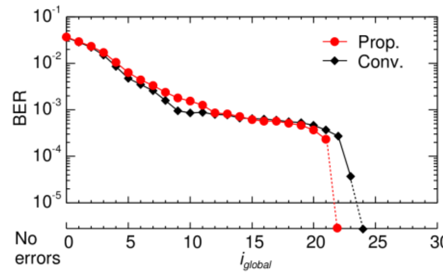

Fig. 6 BER performance for i_{global}.

row weight of 4. The neural network calculates the reliability of $\ln \gamma_k^n$ using the $\ln \gamma_{k-1}^n$, $\ln \gamma_k^n$, and $\ln \gamma_{k+1}^n$. Furthermore, we apply the following parameters $TH_{\gamma m}$ and $W_{\gamma m}$ (m = 0 to 3) for updating $\ln \gamma_n$ according to decoding patterns provided the hard decision of reliability of $\ln \gamma_k^n$. Here, m is the decoding pattern number. The decoding patterns in the cases of m = 0, 1, 2, and 3 correspond to "000" or "111", "001" or "110", "011" or "100", and "010" or "101", respectively. When the reliability, $\ln \gamma_k^n$ is greater than $TH_{\gamma m}$ or smaller than $(1 - TH_{\gamma m})$, it is multiplied by $W_{\gamma m}$. In the proposed GA, the fitness of the l-th individual on the δ-th generation is defined by $f_{\delta l} = -\log_{10}\left(N_{te}^{\delta l}/N_t^{\delta l}\right) - C_{\delta l}\log_{10}\left(1 - N_t^{\delta l}/N_{all}^{\delta l}\right)$. $N_t^{\delta l}$ and $N_{te}^{\delta l}$ are the number of updated targets and the number of update errors, respectively. $N_{all}^{\delta l}$ is the total number of LLRs in row operations. $C_{\delta l}$ is the coefficient that determines the degree to which the number of updates is reflected. We arrange $TH_{\gamma m}$, $W_{\gamma m}$, and $C_{\delta l}$ in one dimension as one chromosome and perform the selection, crossover, and mutation [4]. However, the individuals with the highest fitness are left by applying the elitist preserving selection. We also employ the GA to efficiently explore the optimal weights to enhance the LLRs in column operations and extrinsic information [7].

IV. Performance Evaluation and Conclusion

Now, we compare the performance of the best individuals obtained by the GA. Figure 3 shows the rate of increase in fitness relative to the first generation. Figures 4 and 5 show the selection accuracy of the LLR to be updated and the number of updating targets for generations, respectively. We set i_{sp}= 20, i_{global} = 20, and SNR_S = 21.0 dB. The mark of the red circle indicates the case of the proposed fitness in this study. The mark of the black diamond indicates the case of conventional fitness in [4]. From Fig. 3, the rate of increase in the proposed fitness is greater than the conventional one after the 6th generation. From Figs. 4 and 5, the update accuracy of the proposed fitness is slightly lower than the conventional one, but the overall selection accuracy remains high. On the other hand, the number of updating targets in the proposed fitness remains higher than that in the conventional one after the 6th generation. Figure 6 shows the BER performance for i_{global}. We set i_{sp}= 20 and SNR_S = 21.0 dB. The marks are the same as the previous figures. From Fig. 6, the proposed fitness achieves error-free performance at fewer i_{global} compared to the conventional fitness. From the above, when we employ the GA, setting the fitness to enhance the selection accuracy of the LLR to be updated and the number of updating targets is useful for improving SP decoding performance.

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References

[1] R. Wood et al., "The feasibility of magnetic recording at 10 terabits per square inch on conventional media," *IEEE Trans. Magn.*, vol. 45, no. 2, pp. 917–923, Feb. 2009.

[2] R. G. Gallager, "Low-density parity-check codes," *IRE Trans. Inform. Theory*, vol. 8, pp. 21–28, Jan. 1962.

[3] Y. Nakamura et al., "Suppression of ITI by array head reading and 2D-equalization," *AIP Advances*, vol. 7, no. 5, pp. 056509-1–056509-5, Feb. 2017.

[4] M. Nishikawa et al., "Improvement of SP decoding considering the influence of recording patterns by neural network," *IEEE Trans. Magn.*, vol. 60, no. 9, 3100405, Sept. 2024.

[5] Y. Nakamura et al., "Suppression of ITI by array head reading and 2D-equalization," *AIP Advances*, vol. 7, no. 5, pp. 056509-1–056509-5, Feb. 2017.

[6] P. Robertson et al., "A comparison of optimal and sub-optimal MAP decoding algorithms operating in the log domain", *Proc. IEEE Int. Conf. Commun* (*ICC 1995*), pp.1009–1013, Seattle, USA, June 1995.

[7] M. Nishikawa et al., "A study on applying GA for performance improvement of SP decoder in SMR," *AIP Advances*, vol. 15, 035004, Mar. 2025.