A Linear Support Vector Machine Based Detector for Bit-Patterned Magnetic Recording

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ABSTRACT

The demand for high-capacity storage devices for storing digital information is continuously increasing because of the rapid growth in the number of social media users. Alternative magnetic recording technologies, such as bit-patterned magnetic recording (BPMR), have been proposed in parallel with the current perpendicular magnetic recording technology. However, to increase the areal density in BPMR, we unavoidably encounter the problems of two-dimensional (2D) interference and track mis-registration (TMR). Consequently, to solve these problems, we first present the modified soft-information adjuster (SIA) to mitigate the 2D interference and improve the log-likelihood ratios (LLRs) that were initially produced from the conventional detectors. Then, we propose a linear support vector machine (LSVM)-based detector that works with the modified SIA so as to enhance the reliability of LLRs, which can in turn provide better estimated user bits. Simulation results reveal that the proposed system can yield better bit-error rate performance and is more robust to the TMR effect than the conventional system without the LSVM-based detector.

Keywords: Bit-Patterned Magnetic Recording (BPMR), Linear Support Vector Machine (LSVM), Modified Soft-Information Adjuster (SIA), Track Mis-Registration (TMR)

1. INTRODUCTION

Because of the exponential expansion in the number of users, including data use in social media, cloud-based systems, and other areas on a worldwide scale, the need for high-capacity storage devices for storing huge amounts of digital information is continually rising [1]. Although many high-capacity storage devices, such as hard disk drives (HDD) and solid-state drives (SSD), are available on the market, an HDD operating on the well-known perpendicular magnetic recording (PMR) technology is still a primary data storage device. Nonetheless, due to the superparamagnetic limit or thermal instability on a recording medium, PMR is currently hitting its limit at about 1.0 Tb/in^2 (tera-bits per square inch) [2–3].

Alternative technologies have been continuously developed to overcome the aforementioned restriction. One of these alternative technologies is bit-patterned magnetic recording (BPMR), which has been predicted to provide an areal density (AD) up to 4.0 Tb/in^2 [4]. However, with an increase in AD, bit period and track pitch must be inevitably reduced, which leads to two-dimensional (2D) interference consisting of inter-track interference (ITI) and inter-symbol interference (ISI) [5-6]. Moreover, the smaller bit period and track pitch can easily cause a track mis-registration (TMR) situation, which results in the reader not being able to continuously fly over the center of the desired track [7]. Thus, these issues have a direct impact on data detection and easily degrade system performance.

Accordingly, to overcome the TMR effect, a TMR correction scheme for a multitrack, multihead BPMR system has been proposed [8]. This scheme uses the energy ratio generated from the readback signals of the upper and lower tracks to provide the relationship between the estimated TMR level and the obtained energy ratio. Hence, the pre-designed equalizer associated with the estimated TMR level will be utilized to mitigate the TMR effect. In addition, to cope with the 2D interference, the soft-information adjuster (SIA) was proposed in a two-head, two-track (2H2T) BPMR system [9], which can help improve the log-likelihood ratios (LLRs) obtained from the 2D soft-output Viterbi algorithm (SOVA) detectors. The LLR produced from each main detector will be summed with the estimated LLRs generated from its neighboring detectors. The modified LLRs can yield more reliable results than the original LLRs, thus leading to better bit error rate (BER) performance. The multitrack detection scheme and the hybrid equalizer [10] were also used to improve the BER performance by making ITI and media noise less of a problem. For reliably estimated ITI patterns, a 2D variable equalizer trained with various estimated ITI patterns will be utilized; otherwise, a 2D fixed equalizer that was trained with a pseudorandom bit sequence will be employed. In particular, when TMR and media noise are more severe, the simulation results

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show that the 2D hybrid equalizer can offer a greater signal-to-noise ratio (SNR) than the 2D fixed equalizer.

Currently, many researchers are working to optimize the performance of data storage systems using machine learning (ML) and deep learning (DL) approaches. For example, Jeong et al. proposed detectors that use the multilayer perceptron (MLP) and partial-response maximum-likelihood (PRML) techniques to reduce the effect of 2D interference [11–12]. Furthermore, they have also suggested a bit-flipping scheme by using the K-means algorithm [13–14] to detect and correct bit errors after they are detected by the main data detectors. All of these techniques aim to improve the detection capability and BER performance of data storage systems. Additionally, Nishikawa et al. discovered that using adjacent bit LLRs as the input data to a neural network might enhance the effectiveness of iterative decoding [15–16]. Furthermore, they also found that using the hybrid genetic algorithm to increase the dependability of LLRs made the iterative decoding process more successful [17].

Nonetheless, the deep neural network (DNN) has a high level of complexity [18] compared with a machine learning approach. In this study, therefore, we propose to employ a machine learning approach called a linear support vector machine (LSVM) classification [19] that has much less complexity than the DNN algorithm [20], while still providing good prediction performance. Therefore, we first introduce the modified SIA to improve the LLR reliability that was initially obtained from the conventional 2D SOVA detectors. Here, four 2D SOVA detectors are used instead of two 2D SOVA detectors for the traditional SIA [9]. The three LLRs obtained from the 1st to 3rd detectors are passed to the 1st modified SIA to produce the improved LLR of the 1st desired track, whereas the three LLRs obtained from the 2nd to 4th detectors are also sent to the 2nd modified SIA to produce the improved LLR of the 2nd desired track, respectively.

Next, we propose to adopt the LSVM together with the modified SIA so as to combat the effects of 2D interference and TMR in the BPMR system. Specifically, the LLRs obtained from the modified SIAs will be refined by the LSVM-based detector so as to provide a better set of estimated user bits. Simulation results indicate that the proposed method can definitely enhance the reliability of LLRs. Consequently, the proposed system can achieve a higher detection performance and a better BER performance than conventional recording systems.

The rest of this paper is organized as follows: Section 2 describes the channel model. The proposed scheme is explained in Section 3. Then, the simulation results will be given in Section 4. Finally, the conclusion is summarized in Section 5.

2. CHANNEL MODEL

Fig. 1 depicts the four-head, two-track (4H2T) BPMR channel model consisting of the modified SIA and the LSVM-based detector. The user bits, $x_{l,k} \in \{-1, +1\}$ are recorded on the medium at the l-th track and the k-th bit.

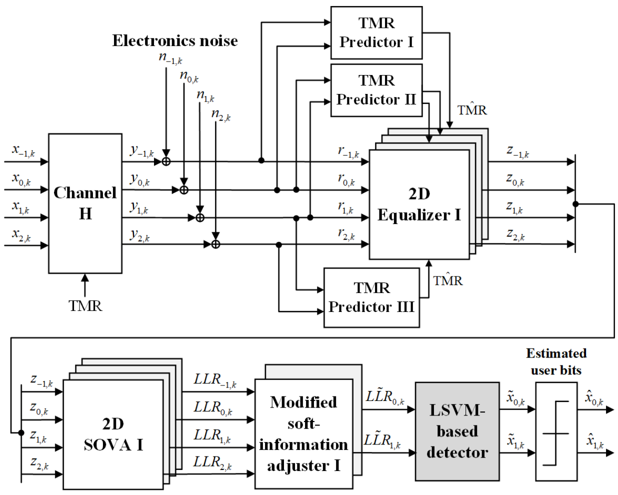


Fig. 1: *A 4H2T BPMR channel model with the modified SIA and the LSVM-based detector for soft-information improvement.*

The readback signals $r_{l,k}$ can be generated from

$$r_{l,k} = x_{l,k} \otimes h_{l,k} + n_{l,k}, \tag{1}$$

where $h_{l,k}$ represents the channel coefficients,$\otimes$ denotes the 2D convolution operator, and $n_{l,k}$ is electronic noise modeled as an additive white Gaussian noise (AWGN) with zero mean and variance σ^2. The channel coefficients, $h_{l,k}$, can be produced from the 2D Gaussian pulse response at integer multiples of the track pitch, T_z, and the bit period, T_x, according to

$$h_{n,m} = P\left(nT_z + \Delta_T, mT_x\right), \tag{2}$$

where

$$P(z,x) = A \exp\left\{-\frac{1}{2c^2}\left[\left(\frac{x+\Delta_x}{\mathrm{PW}_x}\right)^2 + \left(\frac{z+\Delta_z+\Delta_T}{\mathrm{PW}_z}\right)^2\right]\right\}, \tag{3}$$

is the 2D Gaussian pulse response, with x and z being the time indices in the along- and cross-track directions, respectively; Δ_T is the head offset representing the severity of the TMR effect; Δ_x and Δ_z are the position fluctuations, which can be considered as media noise; $A = 1$ is assumed to be the maximum pulse amplitude; PWx and PWz are the width at half maximum of the 2D Gaussian pulse, PW50, in the along- and cross-track directions, respectively; and c =1/2.3548 is the relationship between PW50 and standard deviation of the 2D Gaussian pulse.

In this paper, the signal-to-noise ratio (SNR) considered at the reading point is defined as

$$\mathrm{SNR} = 10\log_{10}\left(\frac{1}{\sigma^2}\right), \tag{4}$$

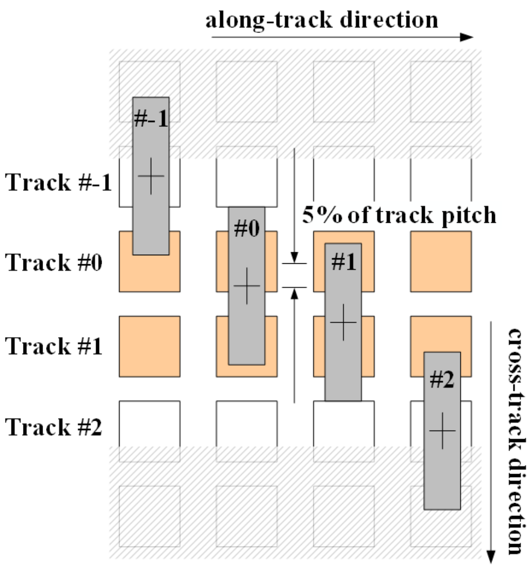


***Fig. 2**: The positions of each read head, where the distance between reader #0 and #1 is reduced by 5% of the track pitch.*

in decibels (dB) [21–22]. In addition, to obtain the suitable read head position for easily finding an impact of TMR [8], the readers #0 and #1 were moved closer to each other by -5% and +5% of the track pitch, respectively, as shown in Fig. 2, whereas the readers #-1 and #2 are still positioned at their center. It should be noted that the TMR effect is evaluated in terms of the percentage of head offset to track pitch, which is defined as

$$\text{TMR (\%)} = \frac{\text{head offset}}{\text{track pitch}} \times 100. \tag{5}$$

At the receiver, four readers are employed to read all four data tracks, resulting in four readback signals, $r_{-1,k}$, $r_{0,k}$, $r_{1,k}$ and $r_{2,k}$, which are then equalized by using the pre-designed 2D equalizers according to the estimated TMR levels obtained from the TMR predictors. Note that the TMR predictor is performed based on the SIA for a 4H2T BPMR system as presented in [20]. Hence, the 2D SOVA detectors are adopted to produce the soft information of user bits (or LLRs) before sending them to the modified SIAs, followed by the LSVM-based detector to improve the reliability of LLRs. Here, three LLRs are generated from each 2D SOVA using the following equations [23–24].

$$\text{LLR} = \Phi_{k+1}^{(\upsilon)}(q) - \Phi_{k+1}^{(\upsilon+1)}(q), \tag{6}$$

where

$$\Phi_{k+1}(q) = \ln\left(-\frac{1}{\sqrt{2\pi\sigma^2}}\right) - \frac{1}{2\sigma^2}\left|z_{l,k} - y(u,q)\right|^2 + \frac{\hat{x}(u,q)\,\lambda_x\left(x_{l,k}\right)}{2}, \tag{7}$$

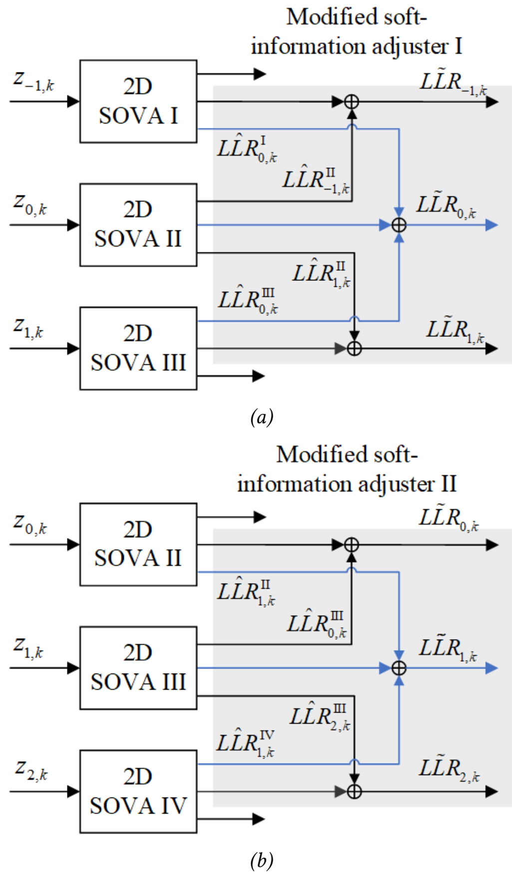


***Fig. 3**: Structures of the modified SIAs that are employed to improve the reliability of LLRs in the 4H2T BPMR system for (a) track #0, $L\tilde{L}L_{0,k}$ and (b) track #1, $L\tilde{L}L_{1,k}$, respectively.*

$\Phi_{(k+1)}^{(\upsilon)}(q)$ represents the transition path υ arriving at state q at time $k+1$, $y(u,q)$ is the noiseless channel output associated with the transition (u,q) according to the trellis diagram, $\hat{x}(u,q)$ is an estimated input data bit according to the transition (u,q), and $\lambda_x(x_{l,k})$ is the apriori probability of the user data bit $x_{l,k}$. Finally, the threshold detector is utilized to determine the estimated user bits $\hat{x}_{0,k}$ and $\hat{x}_{1,k}$.

3. PROPOSED METHOD

Previously, the SIA was proposed to improve the reliability of the LLRs in a 2H2T BPMR system [8]. In this paper, we utilize the SIA technique to improve the LLRs for the 4H2T BPMR system, as demonstrated in Fig. 3. Specifically, the modified SIAs take the LLRs obtained from all four 2D-SOVA detectors, which include the LLR values from neighboring tracks. In Fig. 3(a), for track #0, the $L\hat{L}R^{\mathrm{I}}_{0,k}$ and $L\hat{L}R^{\mathrm{III}}_{0,k}$ values that are produced from the 2D SOVA-I and 2D SOVA-III, respectively, are summed with its soft information, $L\hat{L}R^{\mathrm{II}}_{0,k}$, to obtain the adjusted $L\tilde{L}R_{0,k}$. Similarly, for track #1, the adjusted $L\tilde{L}R_{1,k}$ value is the summation of its soft information, $L\hat{L}R^{\mathrm{III}}_{1,k}$ and its neighboring soft information, $L\hat{L}R^{\mathrm{II}}_{1,k}$

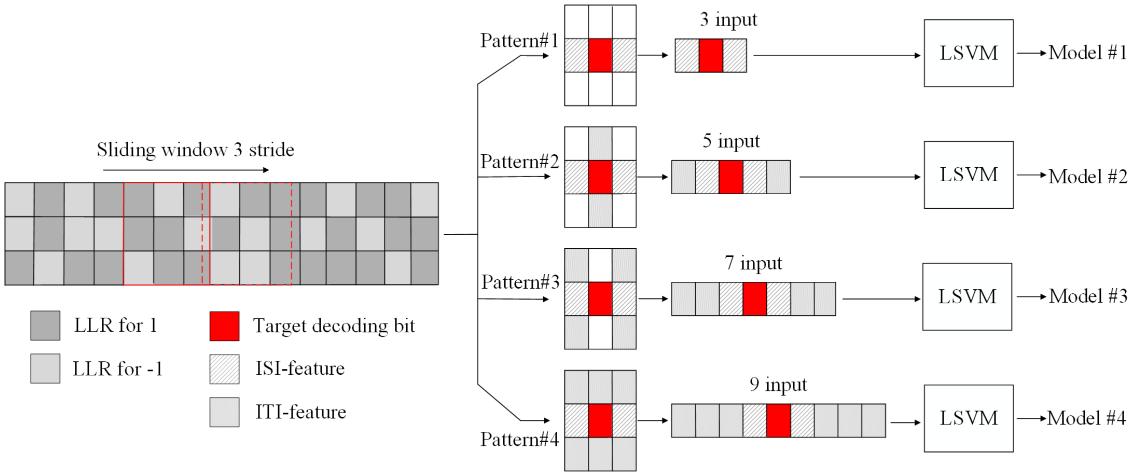


***Fig. 4**: The data preparation structure for training in LSVM.*

and $L\hat{L}R^{\mathrm{IV}}_{1,k}$, produced by 2D SOVA-II and 2D SOVA-IV, respectively, as illustrated in Fig. 3(b). Hence, these adjusted LLRs are sent to the LSVM-based detector to further enhance their reliability for estimating the associated user bits. In this work, the LSVM-based detector utilizes the LSVM classification to learn the refined soft information obtained from the modified SIAs so as to predict the desired soft information, which can be explained in two steps as follows.

3.1 Data Preprocessing

After obtaining the LLRs from the modified SIAs, we consider a 3×3 window with a stride of 3 to prepare the input data for an LSVM learning process, as depicted in Fig. 4. For each 3×3 window, four data patterns corresponding to models #1 to #4 having 3, 5, 7, and 9 bits, respectively, will be considered as the input dataset in the training process. For instance, Model #1 is created to consider only ISI, so it has only 3 input bits in the along-track direction. For Model #2, there are 5 input bits from both along- and cross-track directions, where all four corner bits are ignored, which implies that both ISI and ITI are investigated in this model. In Model #3, almost 9 input bits are fed to LSVM except for the 2 bits from the upper and lower rows of the middle column, so the main ITI effect is neglected in this model. Finally, Model #4 uses all 9 input bits in a training process. Consequently, for a training process, the input bits will be transformed from a 3×3 array to a $1 \times M$ vector before being fed to the LSVM, where M is the number of input bits. We investigate the performance of these four models so as to find out the minimum number of input bits that should be used in the LSVM-based detector while retaining acceptable performance. It should be pointed out that the larger the number of input bits, the longer the time for training the LSVM classification. In this work, 218460 datasets were used for training, which is sufficient for learning the system behavior, and all datasets are generated randomly at SNRs of 5, 10, 15, 20, and 25 dBs.

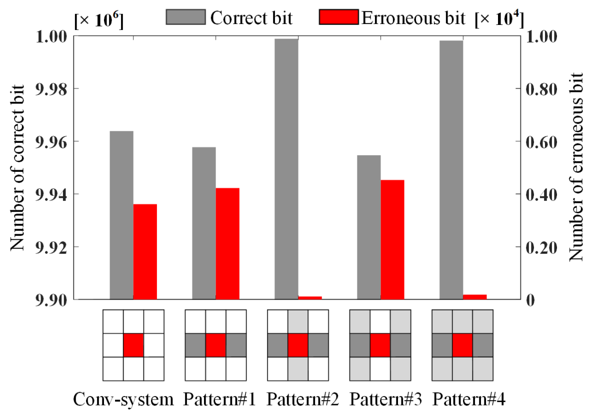


***Fig. 5**: Performances of the proposed systems using different data patterns as the input to the LSVM-based detector in terms of the number of correct and erroneous bits.*

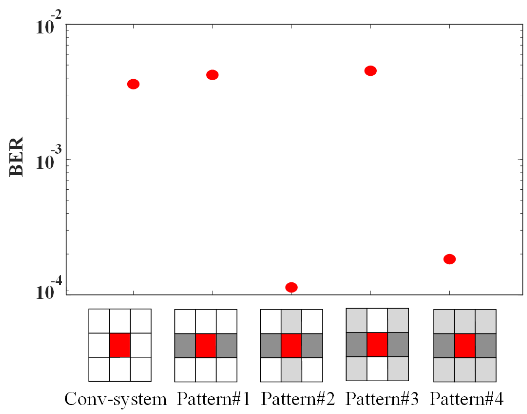


***Fig. 6**: Performance comparison of different systems at SNR = 18 dB and TMR = 0%.*

3.2 LSVM Classification

This paper employs the LSVM classification because it has less complexity than DNN, which involves multiple

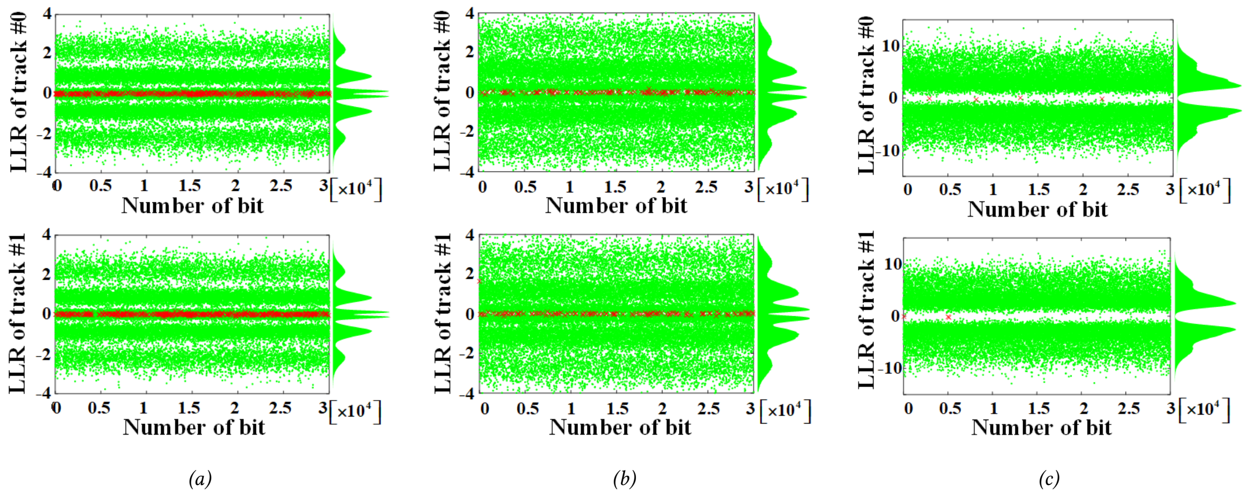


Fig. 7: *LLR distributions of track #0 (top) and track #1 (bottom) at the output of (a) the 2D SOVA detectors, (b) the modified SIAs, and (c) the LSVM-based detectors.*

nodes and layers to construct a neural network for learning and making decisions. Specifically, the LSVM classification uses a hyperplane to accurately divide data points into two categories or classes and maximize the distance between them. Therefore, this LSVM classification is utilized to improve the reliability of LLRs associated with the user bits so as to decode the user bits from the target tracks, i.e., tracks #0 and #1. Generally, the LSVM classification aims to optimize the hyperplane according to [25]

$$\mathbf{w}^{\mathrm{T}}\mathbf{x} + \mathbf{b} = \mathbf{0}, \tag{8}$$

where $\mathbf{w}$ is the classifier vector, i.e., the weight coefficients that we have to search for, T is a transpose operator, $\mathbf{x}$ is the data vector obtained from the modified SIAs, and b is the bias for the best classification performance. In practice, optimizing (8) involves increasing the margin of the classification boundary to the greatest extent possible [20], subject to a certain constraint according to

$$\min_{\mathbf{w}} \frac{\|\mathbf{w}\|^2}{2} + C\sum_i \ell\left(\mathbf{w};\mathbf{x_i},\mathbf{y_i}\right), \tag{9}$$

where $\{\mathbf{x}_i, y_i\}$ for $i = 1, 2, ..., N$ is the training data set, $y_i \in \{-1, +1\}$ is the correct (or labeled) user bit. In (9), the first term shows the regularization term on the classification weights vector, while the second term is related to the classification error, where $\ell(\mathbf{w}; \mathbf{x_i}, \mathbf{y_i}) = \max(1 - y_i\mathbf{w}^{\mathrm{T}}\mathbf{x}_i, 0)$ is the hinge loss used for maximum-margin classification, and C assumed to be 1 is a constant that controls the balance between standardization and error margin. The LSVM can be resolved by using the Lagrangian dual, as explained in [26]. Then, the classifier for LSVM is given by

$$\tilde{x}_{l,k} = \mathbf{w}^{\mathrm{T}}\mathbf{x} + \mathbf{b} = \sum_{\boldsymbol{\alpha}_{\mathbf{i}}} \boldsymbol{\alpha}_{\mathbf{i}}\mathbf{y_i}\left\langle \mathbf{x_i}, \mathbf{x}\right\rangle + \mathbf{b}, \tag{10}$$

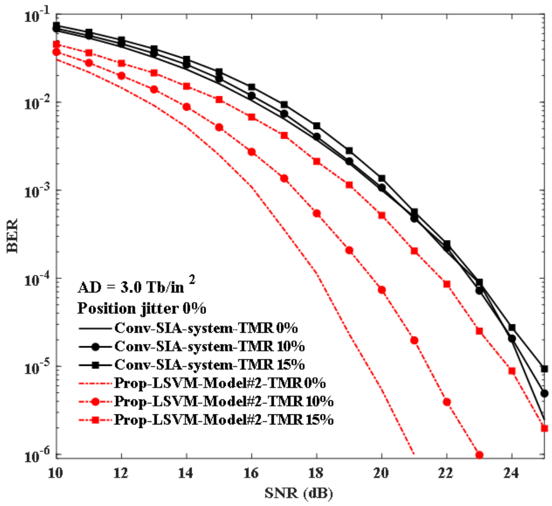
where the weight vector can be computed explicitly by $\mathbf{w} = \sum_{\boldsymbol{\alpha}_{\mathbf{i}}>0} \boldsymbol{\alpha}_{\mathbf{i}}\mathbf{y_i}\mathbf{x_i}$ and used for prediction, α_i is the Lagrangian multiplier, and $\langle \mathbf{x}_i, \mathbf{x}\rangle$ is an inner dot product. Hence, LSVM will predict the target bit of the l-th track and the k-th bit, $\tilde{x}_{l,k}$.

4. RESULTS

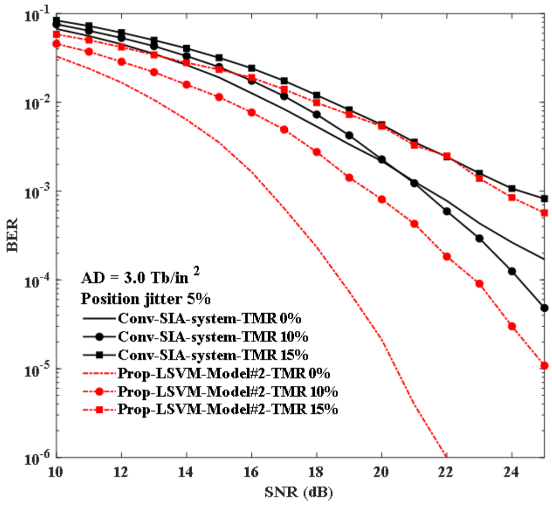
We operate the BPMR channel model at an AD of 3.0 Tb/in^2, where PWx and PWz are 19.4 nm and 24.8 nm, respectively, similar to [22]. Then, we compare the performance of four models, each with a different input data pattern as described in Section 3.1. The simulation was conducted at SNR = 18 dB and TMR = 0%, where 1 million input bits were used for this work.

We first compare the performance of several systems in terms of the number of correct and erroneous bits obtained from the detector, as shown in Fig. 5, where the conventional system denoted as "Conv-system" is the same as the proposed system in Fig. 1 but without the LSVM-based detector. Here, we denote "Pattern#S" as the proposed system using the data pattern #S as the input for the LSVM-based detector. It is clear that Pattern #2 yields the highest number of correct bits and the lowest number of erroneous bits if compared to Pattern #1, Pattern #3, and the conventional system. The reason may be that the provided ISI and ITI information can be sufficiently learned for the LSVM-based detectors, where the information on corner bits can be neglected.

However, we also investigate the influence of corner bits on the learning capability of LSVM-based detectors by considering all corner bits in the training process. We found that Pattern #4 provides a slightly higher BER performance when compared with Pattern #2, which may imply that the corner bit information is not necessary for this training. Specifically, the effect of corner bits on the desired bit looks exiguous when compared with ISI and ITI bits because the corner bits may look far away from the desired bit. On the other hand, although Pattern #4 with all 9 input bits can perform similarly to Pattern #2, Pattern #2 is favored over Pattern #4 to be utilized in the



(a)



(b)

***Fig. 8**: Performance comparison of dierent systems for various TMR levels at AD = 3.0 Tb/in^2 with (a) 0% and (b) 5% media noise.*

4H2T BPMR channel because it has less complexity.

In addition, we also compare the BER performance of different systems at SNR = 18 dB and TMR = 0%, as depicted in Fig. 6. It is apparent that Pattern #2 provides the lowest BER, followed by Pattern #4 and the conventional system. As a result, the LSVM-based detector with a proper input data pattern can help improve the system's performance, and Pattern #2 should be employed in the considered 4H2T BPMR system.

We also investigate the behaviors of the LLR values of two target tracks (i.e., track #0 and track #1) at the three considered outputs, which consist of 1) 2D SOVA detectors, 2) modified SIAs, and 3) LSVM-based detectors, using one million user bits at SNR = 18 dB and TMR = 0%, as illustrated in Fig. 7, where the green dots represent the LLR value associated with the corrected detected user bits and the red cross represents the LLR value associated with the incorrectly detected user bits. Fig. 7(a) displays the distribution of the LLR values at the output of the 2D SOVA detectors for track #0 (top) and track #1 (bottom). Clearly, there are many incorrect LLRs (red crosses) concentrated near zero value, which makes it difficult to distinguish between the user bits "-1" and "+1," thus resulting in 11,636 and 12,132 error bits for track #0 and track #1, respectively.

Similarly, the distribution of the LLR values at the output of the modified SIAs is depicted in Fig. 7(b). As expected, the modified SIA can help enhance the LLR reliability, thus leading to fewer error bits, i.e., 3,610 and 3,609 error bits for track #0 and track #1, respectively. This might be because the incorrect LLRs (red crosses) are scattered wider, which makes it easier to separate between the user bits "-1" and "+1." Furthermore, in Fig. 7(c), we have plotted the LLR associated with the LSVM output so as to compare it with the results in Fig. 7(a) and (b). To achieve this, we employ the method in [27] to train the parameters of an additional sigmoid function to map the LSVM outputs into the posterior probability and then convert it to the LLR, as plotted in Fig. 7(c). It is apparent that the LSVM-based detector can further improve the LLR reliability, thus resulting in much fewer error bits, i.e., 125 and 96 error bits for track #0 and track #1, respectively.

Additionally, if we look at the probability density function (PDF) of the correct LLR values as illustrated on the right-hand side of each figure, the PDF in Fig. 7(c) is explicitly separated into two groups. This means the detector can readily discriminate between the user bits "-1" and "+1," thus leading to much fewer mistake bits if compared with the system without the LSVM-based detector. Consequently, the proposed system with a suitable input data pattern (here, Pattern #2) demonstrates a promising error-correction capability, as the overall BER performance is significantly reduced.

Finally, we then investigate the performance of the proposed system using data pattern #2 as an input to the LSVM-based detector at an AD of 3.0 Tb/in^2 in the presence of TMR and media noise, as shown in Fig. 8. It should be noted that this paper considers only the media noise generated from the position fluctuation. However, the size fluctuation should also be investigated when we need more accurate evaluation results and a more realistic recording model.

In Fig. 8(a) for 0% media noise (position jitter), the proposed system performs better than the conventional system [9] for all TMR levels. We also found in Fig. 8(a) that the TMR effect degrades the performance of all systems, where the larger TMR causes more system degradation. Likewise, a similar conclusion can be obtained when operating the systems in the presence of 5% media noise, as illustrated in Fig. 8(b). Simulation results still indicate that the proposed system can offer better BER performance and is more robust to TMR than the conventional system, even in the presence of media noise.

5. CONCLUSION

In this work, we proposed the modified soft-information adjuster (SIA) and the use of linear support vector machine (LSVM) classification for a four-head, two-track (4H2T) bit-patterned magnetic recording (BPMR) system to deal with the 2D interference and TMR effect so as to enhance the overall system performance. To obtain good bit-error rate (BER) performance with the least amount of system complexity, the modified SIAs are developed to enhance the reliability of log-likelihood ratios (LLRs) obtained from the traditional detectors before sending them to the proposed LSVM-based detector.

Furthermore, a good data pattern that should be employed as the input to the LSVM-based detector was also discovered in this work. The simulation results have shown that the LSVM-based detector can further improve the LLR reliability, especially when a suitable input data pattern is employed, thus leading to better BER performance. In particular, the proposed system performs better and is more robust to the TMR effect than the conventional system without the LSVM-based detector, even in the presence of media noise.

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