Classification of Initial Stripe Height Patterns using Radial Basis Function Neural Network for Proportional Gain Prediction

Prasit Wonglersak, Prakarnkiat Youngkong, and Ittipon Cheowanish

***Abstract*—** This paper aims to improve a fine lapping process of hard disk drive (HDD) lapping machines by removing materials from each slider together with controlling the strip height (SH) variation to minimum value. The standard deviation is the key parameter to evaluate the strip height variation, hence it is minimized. In this paper, a design of experiment (DOE) with factorial analysis by two-way analysis of variance (ANOVA) is adopted to obtain a statistically information. The statistics results reveal that initial stripe height patterns affect the final SH variation. Therefore, initial SH classification using a radial basis function neural network is implemented to achieve the proportional gain prediction.

***Keywords*—** Stripe height variation, Two-way analysis of variance (ANOVA), Radial basis function neural network, Proportional gain prediction.

I. INTRODUCTION

IN fabrication process of hard disk drive (HDD) industries, the dimension of the stripe height (SH) of HDD heads (or sliders) is seriously controlled. Typically, a target of SH after fine lapping which is a very complicated process [1] is about 120-150 nm depend on types of products. A 52 mm long lapping bar which consists of 62 sliders along with Electrical Lapping Guide (ELGs) is attached to a lapping carrier as shown in Fig. 1. Since the SH cannot directly be measured, the ELG height which sensed as electrical resistance, is used for the SH estimation. A lapping carrier which consists of 46 fingers is controlled by pushing or pulling mechanisms for material removal in a lapping machine. Each finger will push or pull accordingly to its corresponding 46 ELG channels. The number of fingers and ELGs is less than the number of sliders in the bar, hence each slider is not directly one-to-one controlled by these corresponding parameters. The objective of lapping is to achieve the minimum SH variation (or sigma) of the bar after finishing the process.

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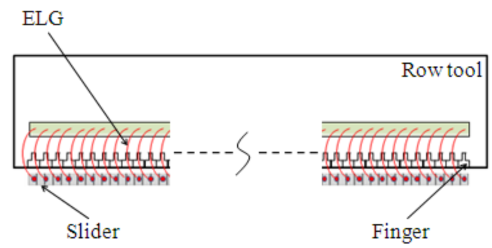

Fig. 1 A bar is attached to a lapping carrier.

The original concept of controlling the lapping carrier is a proportional-integral-derivative (PID) controller [2], [3]. However, the proportional controller is only mode used to calculate forces for each finger by applying the following equation.

$$F(i) = Kp \bullet e(i) \ ,$$

where F(i) is an applied force on finger ith,
e(i) is an error of finger ith and
Kp is the proportional gain.

According to the equation, for each round of the calculation, the error is computed as shown.

$$e(i) = x - resF(i) \ ,$$

where x is an average value of resF and
resF(i) is a resistance value detected at finger ith.

In general, different techniques have been used for obtaining appropriate values of the proportional gain [4]-[6]. However, in practical uses, especially with sophisticated lapping machines where a classical systematic model cannot be established, these choices may not be effective. Hence, the alternative of tuning the proportional gain is proposed in this paper.

This paper is organized as follows. A design of experiment (DOE) with factorial analysis by two-way analysis of variance (ANOVA) is described in section II. It is useful to analyze the enormous data by statistical techniques to show that an initial SH of each bar affects significantly the final stripe height variation. Section III presents an initial SH classification using a radial basis function neural network for the proportional gain prediction. Conclusion and future work are provided in section IV.

II. Two-way ANOVA

In order to see whether the initial SH patterns have a significant impact on the final SH variation of the lapping process, the two-way ANOVA [7] is implemented as follows.

A. Collecting the initial SH data

The SH data is collected only from one lapping machine which is working on only one product specification to optimize the environment.

1. The lapping machine is used the proportional gain (Kp) of 40, 60 and 80 in the process. Considering a confounding effect, the value of Kp is changed every 10 bars until 300 data set are obtained.

2. Problems of outliers, for instance SH no.28 in Fig.2, presented at the beginning of the lapping process, are screened out.

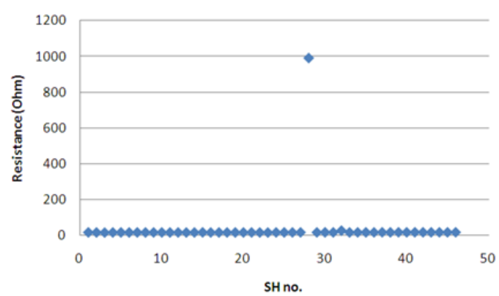

Fig. 2 A data set contains an abnormal SH value.

B. Dividing the data into 3 groups

1. Implementation details:

An initial SH data is the resistance values of thirty-eight sliders along the bar which are measured by the ELGs before the lapping machine starts lapping. Using a polynomial regression technique from order 2 up to order 9, the initial SH patterns of each data set is obtained. A coefficient of determination, R2, is used as a threshold for data classification. If the R2 value is greater than the threshold value, the regression process is then terminated.

2. Determination of threshold:

Three threshold values which are 0.6, 0.55 and 0.5, are proposed at the beginning. But, after completing the whole experiments, 0.5 is the most suitable threshold value while it yields equal numbers of data set in 3 groups as follow:

- Low-order group: Fitted order is 2-3.
- Medium-order group: Fitted order is 4-9, and
- High-order group: Fitted order is greater than 9.

C. Implementing Two-way ANOVA

1. Data table:

Kp and groups of initial SH patterns are independent variables, and final SH variations are dependent variables. Table 1 shows combinations of them.

TABLE I
Data table for two-way ANOVA

Kp	Initial SH pattern group		
	Low-order	Medium-order	High-order
40			
60			
80			

2. Result:

According to the F-value in Table II, both Kp values and groups of initial SH patterns affect significantly the final SH variation. Furthermore, it shows a significant interaction between them.

TABLE II
Result of two-way ANOVA

Source	SS	df	MS	F	P-value	F crit
Kp	52.911	2	26.455	10.481	0.0001	3.068
Initial SH pattern group	36.659	2	18.329	7.262	0.0010	3.068
Interaction	27.973	4	6.993	2.771	0.0301	2.444

III. Implementing a radial basis function neural network

From the result computed by two-way ANOVA, it confirms that the initial SH patterns and Kp values affect the final SH variation, significantly, and there are interactions between them. Hence, the initial SH patterns are selected to be an input parameter for the radial basis function neural network to compute the Kp value.

A. Theory of radial basis function network

In general, the RBF neural network [8], [9] consists of three layers as shown in Fig. 3. The transformation from the input layer to the hidden layer which consists of a radial basis function is nonlinear. On the other hand, the output layer performs linear transformation to calculate the output. There are several forms of the radial basis function, however the most common chosen is a Gaussian function.

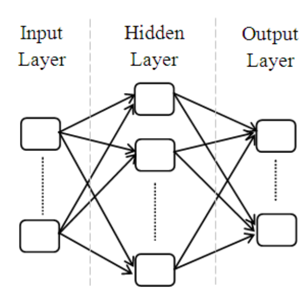

Fig. 3 The RBF neural network architecture

B. Radial basis function neural network model for proportional gain prediction

For creation of the RBF network, the network is trained by supervised learning technique with the input and target data which present a low SH variation. The input parameters are the initial SH patterns while the output parameters are the corresponding Kp as shown in Fig. 4.

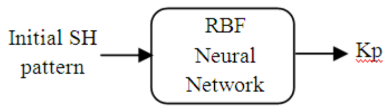

Fig. 4 The trained model of RBF neural network

The RBF neural network model is implemented on Neural Network Toolbox (NN Tool) of Matlab. The 138 data set is used for training the model. The performance of model is shown in Fig. 5.

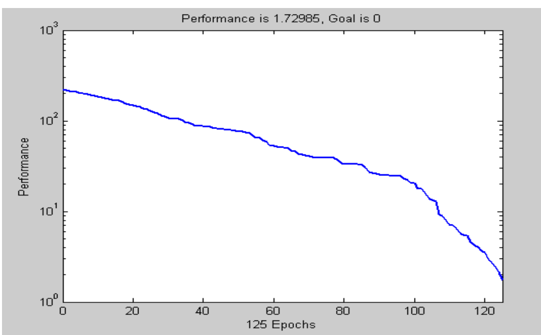

Fig. 5 Performance result of RBF model, Neurons = 125, MSE = 1.72985

For testing, 35 lapping bars are randomly taken from the HDD lapping process to verify the RBF neural network model. Using the learning of RBF neural network model based on 138 supervised data sets, Kp for each lapping bar is calculated accordingly to each initial SH pattern. After finishing the experiments, they all yields low SH variation.

IV. CONCLUSION AND FUTURE WORK

The initial SH classification using the RBF neural network has been evaluated in the HDD lapping process. The result shows that desirable values of the final SH variations are obtained. Since the present work focus only on the proportional gain or Kp, integral and derivative controllers shall be discussed and developed in a very close future.

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