Quality control in hard disc drive manufacturing using pattern recognition technique

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Abstract. Computerized monitoring-diagnosis is an efficient technique to identify the source of unnatural variation (UV) in manufacturing process. In this study, a pattern recognition scheme (PRS) for monitoring-diagnosis the UVs was developed based on control chart pattern recognition technique. This PRS integrates the multivariate exponentially weighted moving average (MEWMA) control chart and artificial neural network (ANN) recognizer to perform two-stage monitoring-diagnosis. The first stage monitoring was performed using the MEWMA statistics, whereas the second stage monitoring-diagnosis was performed using an ANN. The PRS was designed based on bivariate process mean shift between 0.75σ and 3.00σ, with cross correlation between ρ=0.1 and 0.9. The performance of the proposed PRS has been validated in quality control of hard disk drive component manufacturing. The validation proved that it is efficient in rapidly detecting UV and accurately classify the source of UV patterns. In a nutshell, the PRS will aid in realizing automated decision making system in manufacturing industry.

1. Introduction

Statistical process control is a study about quality control management in the field of manufacturing and processing. In statistical process control, there are 7 basic control tools such as check sheet, Pareto diagram, cause and effect diagram, histogram, scatter diagram, control chart and flow chart. These control tools had been widely used in manufacturing industries to minimize process variation that impair efficiency through identification of root cause errors[1]. Statistical process control is a statistical method of separating variation resulting from special causes from natural variation and to establish and maintain consistency in the process, enabling process improvement.

Each root caused error or source of variation will produced a set of specific chart pattern. These chart patterns can be recognized and the type of unnatural variation can be identified. This scheme serves as purpose to identify the out of control condition and represents them in the form of output control chart pattern. There are a total seven control chart patterns, namely normal, stratification, upshift, downshift,

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systematic, cyclic, upwards trend, downwards trend. However, the main focus of this research will be on normal and shift pattern only.

![Control chart pattern for univariate process](image)

**Figure 1:** Control chart pattern for univariate process [2]

The type of analysis used in this research is bivariate analysis. In other words, there are two input data $X_1$ and $X_2$. Input pattern and representation is an approach to represent input signal of patterns into an ANN recognizer. There are three types of input representation techniques which are raw data based, featured based and wavelet de-noise input representation [2]. The input pattern and representation of this research is featured based. It utilizes the unique characteristic of the data and extract significant properties so that it reduces dimensional input vectors, computational efforts and time consuming for training ANN recognizer [3].

![Comparison between raw data based and featured data based](image)

**Figure 2:** Comparison between raw data based and featured data based [2]

2. Research Methodology

The framework (a) and training result (b) of the pattern recognition scheme (PRS) is shown in Figure 3. Three steps are involved: generator for training data, training of ANN recognizer, and validation.

2.1 Generation for training data

In bivariate quality control, two (2) correlated quality variables (X1, X2) are monitored-diagnosed simultaneously. The sources of UV can be represented by seven pattern categories namely N00, US10, US01, US11, DS10, DS01, and DS11. N, U and D represent Normal, Upward Shifts and Downward Shifts respectively. Pattern N00 represents in-control in both X1 and X2. Patterns US10 and DS10 represent there is UV (upward or downward shifts) in X1, while X2 remain in control. Inversely, patterns US01 and DS01 represents there is UV (upward or downward shifts) in X2, while X1 remain in control. In other cases, patterns US11 and DS11 represents there are UV (upward or downward shifts) in both X1 and X2. All patterns were model and simulated using the established mathematical equations [3].
2.2 Training for ANN recognizer

Target performances were set at $\geq 99\%$ for pattern N00 and at $\geq 95\%$ for patterns US10 and others. The ANN architecture consists of 14 neurons in input layer, 22 neurons in hidden layers and 7 neurons in output layer. The training can be performed within 1 minute and 50 seconds.

2.3 Validation

In order to ensure that the scheme is applicable in real world, the performance of the scheme was validated in quality control of hard disc drive (HDD) component manufacturing. HDD is a mechanism that reads and writes data, and then stores the written data into it. The components of a hard disk drive consists of casing, base casting, spacer ring, platter, spindle motor, motor axis and top cap as shown in Figure 4.

Figure 3: Framework of pattern recognition scheme (PRS)

Figure 4: Hard disk drive assembly [4]
The sources of UV in HDD component manufacturing are caused by loading error, offsetting tools and inconsistent pressure. The bivariate correlated quality variables being monitored-diagnosed are positioning (X1 or P) and concentricity (X2 or C). These variables are also known as Critical-to-Quality (CTQ) features. Figure 5 shows the graphical representation of control chart patterns for each source of UV.

The work piece of base casting is automatically loaded into pneumatic fixture using a robotic system. Inconsistent pressure due to problem in pneumatic system will cause upward shifts in both CTQ features (US11) at high correlation ($\rho > 0.4$). Further discussion on loading error and offsetting tools can be found in [4].

### Table 1

|                | Positioning | Concentricity |
|----------------|-------------|---------------|
| In-control     | Normal      | Normal        |
| Loading error  | Upward Shift| Normal        |
| Offset tool    | Normal      | Upward Shift  |
| Inconsistent pressure | Upward Shift | Upward Shift |

**Figure 5:** Source of UV and its control chart pattern [4]

3. **Results and Discussion**

Discussion is focused on validation performance of inconsistent pressure. The mean ($\mu$) and standard deviation ($\sigma$) of multivariate in-control process were determined based on the first 24 samples (observations 1st ~ 24th). Inconsistent pressure begins between observation samples 31st ~ 50th. The monitoring-diagnosis performance results are summarized in Table 1, whereby the determinations of process condition (monitoring) and source variables of mean shifts (diagnosis) are based on outputs of the framework as shown in Table 2.

In the first 30 samples, the PRS was able to correctly identify the bivariate process data streams as in normal patterns (N). This means that this PRS was effective to identify bivariate in-control process without triggering any false alarm.

Inconsistent pressure in pneumatic system begins at sample 41st. In relation to out-of-control detection capability, the PRS can be observed as sensitive to detect bivariate process mean shifts rapidly as upward-shift patterns (US11) starting from sample 32nd (at window range 9th ~ 32th). In diagnosis aspect, this PRS framework can be observed as effective to classify the source variables of mean shifts without mistake.
Table 1: Monitoring-diagnosis performance decision

| No. | Original sample | Standardized sample | Window range (WR) | FRD decision |
|-----|-----------------|---------------------|-------------------|--------------|
|     | X1 | X2 | Z1 | Z2 |               |               |
| 1   | 0.0608 | 0.0743 | 0.6507 | 1.4586 | - | - |
| 2   | 0.0407 | 0.0502 | -0.5593 | 0.0150 | - | - |
| 3   | 0.0595 | 0.0617 | 0.5684 | 0.7034 | - | - |
| 4   | 0.0326 | 0.0617 | -1.0469 | 0.7020 | - | - |
| 5   | 0.0519 | 0.0487 | 0.1133 | -0.0790 | - | - |
| 6   | 0.0178 | 0.0314 | -1.9321 | -1.1146 | - | - |
| 7   | 0.0424 | 0.0271 | -0.4531 | -1.3719 | - | - |
| 8   | 0.0580 | 0.0297 | 0.4812 | -1.2180 | - | - |
| 9   | 0.0453 | 0.0379 | -0.2849 | -0.7243 | - | - |
| 10  | 0.0707 | 0.0684 | 1.2390 | 1.1067 | - | - |
| 11  | 0.0402 | 0.0377 | -0.5885 | -0.7406 | - | - |
| 12  | 0.0126 | 0.0090 | -2.2459 | -2.4614 | - | - |
| 13  | 0.0304 | 0.0582 | -1.7159 | 0.4912 | - | - |
| 14  | 0.0677 | 0.0507 | 1.0620 | 0.0400 | - | - |
| 15  | 0.0486 | 0.0511 | -0.0816 | 0.0652 | - | - |
| 16  | 0.0567 | 0.0559 | 0.4002 | 0.3517 | - | - |
| 17  | 0.0659 | 0.0571 | 0.9530 | 0.4271 | - | - |
| 18  | 0.0159 | 0.0389 | -2.0455 | -0.6648 | - | - |
| 19  | 0.0400 | 0.0420 | -0.6016 | -0.4787 | - | - |
| 20  | 0.0390 | 0.0188 | -0.6599 | -1.8729 | - | - |
| 21  | 0.0339 | 0.0261 | -0.9670 | -1.4318 | - | - |
| 22  | 0.0475 | 0.0546 | -0.1490 | 0.2738 | - | - |
| 23  | 0.0753 | 0.0462 | 1.5173 | -0.2281 | - | - |
| 24  | 0.0499 | 0.0463 | -0.0085 | -0.2193 | 1~24 | N |
| 25  | 0.0705 | 0.0486 | 1.2301 | -0.0865 | 2~25 | N |
| 26  | 0.0391 | 0.0268 | -0.6520 | -1.3927 | 3~26 | N |
| 27  | 0.0506 | 0.0359 | 0.0365 | -0.8486 | 4~27 | N |
| 28  | 0.0377 | 0.0385 | -0.7368 | -0.6901 | 5~28 | N |
| 29  | 0.0601 | 0.0606 | 0.6034 | 0.6379 | 6~29 | N |
| 30  | 0.0464 | 0.0481 | -0.2166 | -0.1141 | 7~30 | N |
| 31  | 0.0916 | 0.1074 | 2.4989 | 3.4435 | 8~31 | N |
| 32  | 0.0947 | 0.0879 | 2.6829 | 2.2761 | 9~32 | US(1,1) |
| 33  | 0.0825 | 0.0603 | 1.9525 | 0.6207 | 10~33 | US(1,1) |
| 34  | 0.0983 | 0.0941 | 2.8991 | 2.6482 | 11~34 | US(1,1) |
| 35  | 0.1215 | 0.1084 | 4.2886 | 3.5050 | 12~35 | US(1,1) |
| 36  | 0.0924 | 0.0957 | 2.5425 | 2.7418 | 13~36 | US(1,1) |
| 37  | 0.0836 | 0.0936 | 2.0176 | 2.6189 | 14~37 | US(1,1) |
| 38  | 0.0987 | 0.1149 | 2.9226 | 3.8944 | 15~38 | US(1,1) |
| 39  | 0.0847 | 0.0773 | 2.0839 | 1.6386 | 16~39 | US(1,1) |
| 40  | 0.0658 | 0.0795 | 0.9460 | 1.7719 | 17~40 | US(1,1) |
| 41  | 0.0917 | 0.0900 | 2.5042 | 2.3994 | 18~41 | US(1,1) |
| 42  | 0.0837 | 0.0762 | 2.0243 | 1.5729 | 19~42 | US(1,1) |
| 43  | 0.0793 | 0.1177 | 1.7589 | 4.0612 | 20~43 | US(1,1) |
| 44  | 0.1046 | 0.0934 | 3.2781 | 2.6056 | 21~44 | US(1,1) |
| 45  | 0.1142 | 0.0803 | 3.8523 | 1.8154 | 22~45 | US(1,1) |
| 46  | 0.0753 | 0.1094 | 1.5179 | 3.5670 | 23~46 | US(1,1) |
| 47  | 0.0855 | 0.0919 | 2.1304 | 2.5142 | 24~47 | US(1,1) |
| 48  | 0.0706 | 0.0600 | 1.2389 | 0.5988 | 25~48 | US(1,1) |
| 49  | 0.0949 | 0.1021 | 2.6949 | 3.1245 | 26~49 | US(1,1) |
| 50  | 0.0453 | 0.0841 | -0.2844 | 2.0470 | 27~50 | US(1,1) |

Note: \( \mu_1=0.0460, \mu_2=0.0452, \sigma_1=1.658 \times 10^{-2}, \sigma_2=1.559 \times 10^{-2} \)
Table 2: Output of the PRS in relation to the monitoring-diagnosis decision

| PRS     | N(0,0) | US(1,0) | US(0,1) | US(1,1) | DS(1,0) | DS(0,1) | DS(1,1) |
|---------|--------|---------|---------|---------|---------|---------|---------|
| 1-24    | 0.3109 | 0.2077  | 0.0085  | 0.0462  | 0.0070  | 0.0094  | 0.0067  |
| 2-25    | 0.5505 | 0.423   | 0.0794  | 0.049   | 0.0070  | 0.0094  | 0.0067  |
| 3-26    | 0.0239 | 0.0160  | 0.0068  | 0.0070  | 0.0070  | 0.0070  | 0.0070  |
| 4-27    | 0.0489 | 0.0141  | 0.0070  | 0.0070  | 0.0070  | 0.0070  | 0.0070  |
| 5-28    | 0.0127 | 0.0102  | 0.0070  | 0.0070  | 0.0070  | 0.0070  | 0.0070  |
| 6-29    | 0.0127 | 0.0102  | 0.0070  | 0.0070  | 0.0070  | 0.0070  | 0.0070  |
| 7-30    | 0.0127 | 0.0102  | 0.0070  | 0.0070  | 0.0070  | 0.0070  | 0.0070  |
| 8-31    | 0.0127 | 0.0102  | 0.0070  | 0.0070  | 0.0070  | 0.0070  | 0.0070  |
| 9-32    | 0.0127 | 0.0102  | 0.0070  | 0.0070  | 0.0070  | 0.0070  | 0.0070  |

Note: Bold value represents the maximum output of ANN that determines pattern category.

4. Conclusion
The main focus of this research is to design a scheme for recognizing control chart patterns in the manufacturing of hard disk drive component. This paper investigated the PRS performance in monitoring-diagnosis the source of unnatural variation (UV) in bivariate process. Based on the inconsistent pressure as the source of UV, the proposed PRS is capable to rapidly identify the bivariate in-control process condition (N00 pattern) without triggering any false alarm. In addition, it is also effective in accurately classifying the source of UV (US11) without mistake. Since this research is focused on mean shifts causal patterns, further research will be extended to other causal patterns such as trends and cyclic.

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