

Recognition of control chart patterns with incomplete samples

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Abstract. In quality control, automated recognition of statistical process control (SPC) chart patterns is an effective technique for monitoring unnatural variation (UV) in manufacturing process. In most studies, focus was given on complete patterns by assuming there is no constrain in the SPC samples. Nevertheless, there is in-practice case whereby the SPC samples cannot be captured properly due to measurement sensor error or human error. Thus, this research aims to design a recognition scheme for incomplete samples pattern that will be useful for an industrial application. The design methodology involves three phases: (i) simulation of UV and SPC chart patterns, (ii) design of pattern recognition scheme, and (iii) evaluation of performance recognition. It involves modelling of the simulated SPC samples in bivariate quality control, raw data input representation, and recognizer training and testing. The proposed technique indicates a high recognition accuracy (normal pattern = 99.5%, shift patterns = 97.5%). This research will provide a new perspective in SPC charting scheme when dealing with constraint in terms of incomplete samples, which is greatly useful for an industrial practitioner in finding the solution for corrective action.

1. Introduction

In modern manufacturing process, unnatural process variation (UV) need to be identified, minimized, and eliminated in order to avoid poor quality product, production capacity decrement, and delivery lateness. The typical sources of UV are vibration, machine breakdown, inconsistent materials, and lack of operators. In order to reduce variability, improvement in process monitoring and diagnosis are the key issues. Statistical process control (SPC) tools such as control charting schemes have been widely used for this purpose. The traditionally SPC chart was designed only for detecting an out-of-control condition in manufacturing process. Later, interpretation of control chart patterns (CCPs) has been given more attention in research since it is more informatics in finding the source of UV [1, 2]. This was greatly useful for an industrial practitioner such as quality inspector or production foreman in finding the root cause error and solution for corrective action. Each source of UV can be indicated by a specific CCPs. Figure 1 shows several types of CCPs: normal, stratification, upward shifts, downward shifts, systematic, cyclic, upwards trend, and downwards trend.



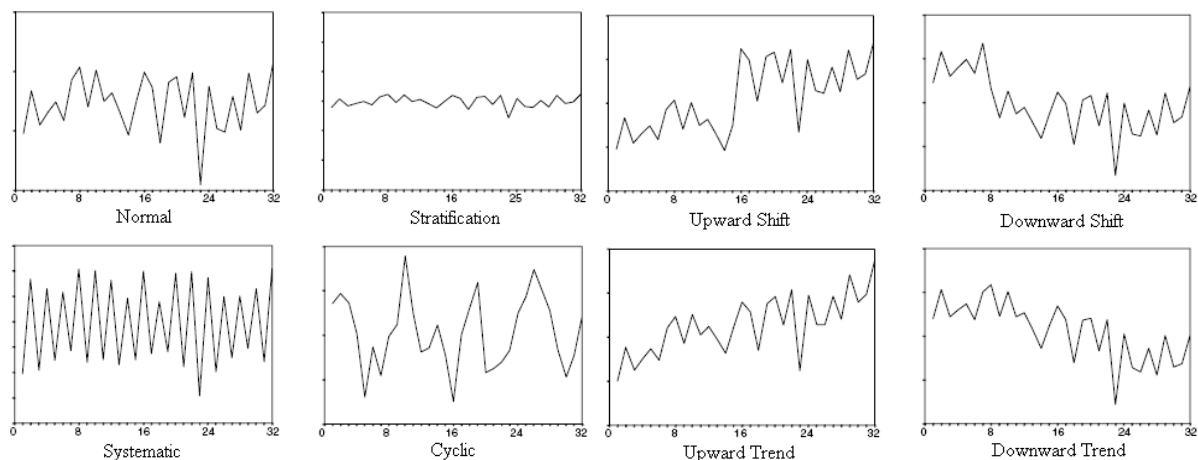


Figure 1: SPC chart pattern [3]

When a product feature involves two correlated variables (bivariate), simultaneous or dependent monitoring-diagnosis for these variables is necessary. Inversely, monitoring-diagnosis independently will lead to erroneous result. For instance, positioning and concentricity of hole are bivariate for motor assembly [4]. Dependent monitoring approach is capable of detecting unusual sample with respect to the other samples based on joint control region, while independent monitoring approach is nearly impossible to detect an assignable cause in the presence of bivariate correlated samples [5].

In the related study, incomplete samples or missing data is an issue in interpretation of CCPs. This can happen due to many reasons such as errors in measuring sensor or human errors. For instance, an operator drop out the work piece before the test ends. In order to identify the CCPs with incomplete samples, this research proposes a design of pattern recognition scheme by forecasts the missing samples before it can be identified using a pattern recognizer. This paper is organized as follows: Section 2 describes the design methodology of pattern recognition scheme. Simulation of UV and SPC chart patterns are presented in Section 2.1. Design of pattern recognition scheme and evaluation of performance recognition are discussed in Sections 2.2 and 2.3 respectively. Finally, the conclusions are outlined in Section 3.

2. Methodology

Research methodology involves: (i) simulation of unnatural variation and SPC chart patterns, (ii) design of pattern recognition scheme, and (iii) evaluation of performance recognition.

2.1 Simulation of unnatural variation and SPC chart patterns

Simulation on unnatural variation (UV) was focused on bivariate process, which involved two correlated variables (X_1 , X_2) that need to be monitored simultaneously. It is also known as bivariate quality control. In various cases, the UV can be indicated by 7 pattern categories such as N00, US10, US01, US11, DS10, DS01, and DS11. Symbols N, US and DS represent normal, upward shifts and downward shifts. N00 represents pattern for a statistically in-control process, whereby average samples for both variables lie at the central line of SPC chart. US10 or DS10 represent patterns for a statistically out-of-control, whereby there is UV (upward or downward shifts) in X_1 , while X_2 remains in statistically in-control. Inversely, US01 or DS01 indicates there is UV (upward or downward shifts) in X_2 , while X_1 remains in-control. In other cases, US11 or DS11 shows there are UV (upward or downward shifts) in both variables. These patterns can be model using the following mathematical equations.

Step 1: Generate the random samples for process variable 1 (Y_1) with in-control mean (μ_1) and standard deviation (σ_1):

$$Y_1 = \mu_1 + n_1 \sigma_1 \quad (1)$$

Step 2: Generate the random samples for process variable 2 (Y_2), which is correlated to Y_1 . μ_2 and σ_2 are the in-control mean and standard deviation for Y_2 , whereas ρ is the correlation coefficient between the two process variables.

$$Y_2 = \mu_2 + [n_1 \rho + n_2 \sqrt{(1 - \rho^2)}] \sigma_2 \quad (2)$$

Step 3: Transform the random samples to be a normal or a shift pattern to represent real SPC samples (X_1, X_2). The magnitude of mean shift (h) is expressed in standard deviation of stable process (σ_{01}, σ_{02}):

$$X_1 = h_1 (\sigma_{01}/\sigma_1) + Y_1 \quad (3)$$

$$X_2 = h_2 (\sigma_{02}/\sigma_2) + Y_2 \quad (4)$$

A pair observation sample (X_1, X_2) represents a bivariate vector measured at time t (X_t) that follows the random normal bivariate distribution $N(\mu_0, \Sigma_0)$. μ_0 and $\Sigma_0 = [(\sigma_1^2 \ \sigma_{12}) (\sigma_{12} \ \sigma_2^2)]$ are the mean vector and the covariance matrix for bivariate stable process with variances (σ_1^2, σ_2^2) and covariance ($\sigma_{12} = \sigma_{21}$).

A case study in manufacturing of hard disc drive (HDD) components showed that the simulated SPC chart patterns can be applied in manufacturing industry. HDD is a mechanism that reads and writes data, and then stores the written data into it. The HDD consists of casing, base casing, spacer ring, platter, spindle motor, motor axis and top cap as shown in Figure 2a. The UV in based casing manufacturing can be caused by loading error, offsetting tools and inconsistent pressure. The bivariate quality variables being monitored-diagnosed are positioning (X_1) and concentricity (X_2).

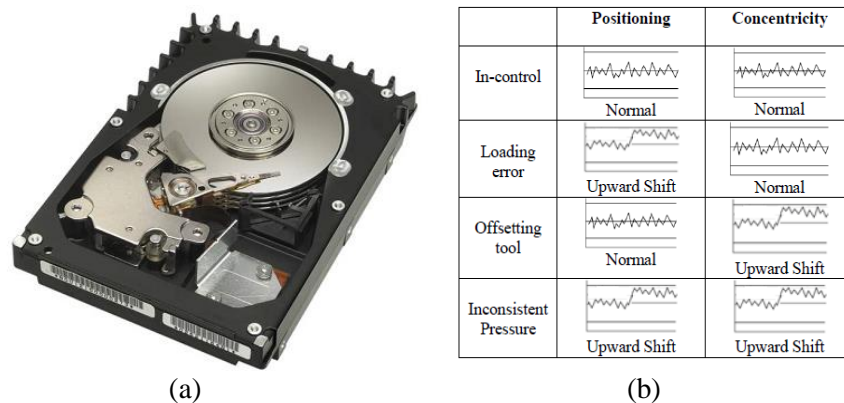


Figure 2: HDD assembly and SPC chart pattern [4]

Figure 2b shows the graphical representation of SPC chart patterns for each 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].

2.2 Design of Pattern Recognition Scheme

The framework of the pattern recognition scheme is shown in Figure 3a. Simple moving average (SMA) was utilized as the forecasting or prediction technique for incomplete SPC sample. An artificial neural network (ANN) with 3 layers perceptron model, raw data input representation, and gradient decent with momentum and adaptive learning rate was utilized as the pattern recognizer. The setting parameters for ANN model is shown in Figure 3b, and the following mathematical equations:

SMA: Incomplete SPC sample (Y_p) is predicted by averaging the 3 previous samples (X_{p-1} , X_{p-2} , X_{p-3}):

$$X_p = (X_{p-1} + X_{p-2} + X_{p-3}) / 3 \quad (5)$$

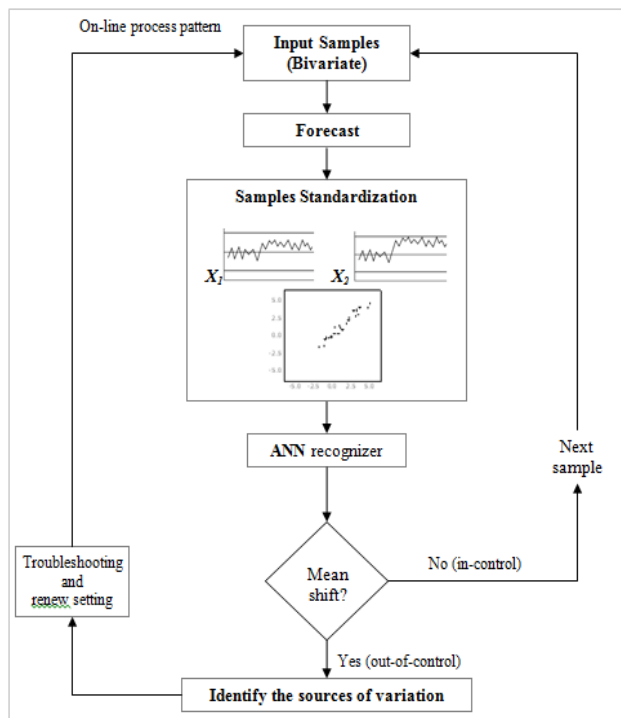
Sample standardization: SPC samples are rescaled to a standardize range, i.e., within $[-3, +3]$:

$$Z_1 = (X_1 - \mu_{01}) / \sigma_{01} \quad (6)$$

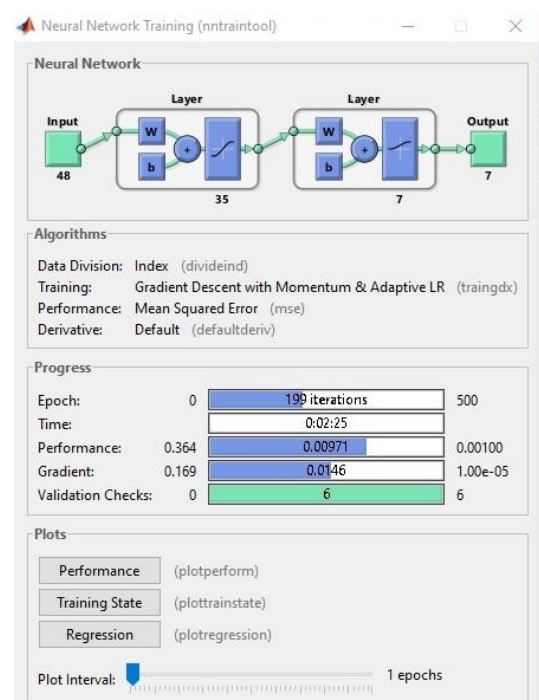
$$Z_2 = (X_2 - \mu_{02}) / \sigma_{02} \quad (7)$$

A pair standardized sample (Z_1 , Z_2) represents a standardized bivariate vector measured at time t (Z_t) that follows the standardized normal bivariate distribution $N(0, R)$. Zero and $R = [(1 \ \rho) (\rho \ 1)]$ are the mean vector and a general correlation matrix for bivariate stable process with unity variances ($\sigma_1^2 = \sigma_2^2 = 1$) and covariance equal to cross correlation ($\sigma_{12} = \sigma_{21} = \rho$).

Input representation: The raw data input representation consists of 24 consecutive standardized samples for both quality variables. Each SPC chart pattern is represented by 48 input samples (i.e., Z_{1-V1} , Z_{1-V2} , ..., Z_{24-V1} , Z_{24-V2}), where $V1$ and $V2$ denote variable 1 and variable 2 respectively.



(a) Framework



(b) Training result

Figure 3: Pattern recognition scheme and its setting parameters

2.3 Evaluation of Performance Recognition

Based on screening simulation, the target performances were set at $\geq 99\%$ for normal pattern (N00) and at $\geq 95\%$ for overall shift patterns (US10, US01, US11, DS10, DS01, DS11). The training results are summarized in Table 1. The highest recognition accuracy was achieved at 35 neurons of hidden layer (HLN) within 2 minute and 25 seconds. The training result is improving in-line with the increment of HLN. The lowest MSE (4.47, 5.69) were achieved at HLN = 15 and 40 respectively. However, it shows lower recognition accuracy compared to HLN = 35. In other point of view, one can see that this ANN recognizer requires a high computational time when the neurons number is increased.

Table 1: Training results

| Number of hidden neuron (HN) | Recognition accuracy (%) | | MSE $\times 10^{-3}$ | MSE | Epoch | Time (sec) |
|------------------------------|--------------------------|----------------|----------------------|---------------|------------|-------------|
| | Normal pattern | Shift pattern | | | | |
| 15 | 97.9320 | 99.0234 | 4.47 | 0.00447 | 257 | 1.59 |
| 20 | 99.2612 | 95.5987 | 19.942 | 0.019942 | 153 | 1.19 |
| 26 | 97.7882 | 86.9540 | 29.85 | 0.02985 | 133 | 1.20 |
| 30 | 98.8697 | 98.4877 | 9.590 | 0.009590 | 190 | 2.10 |
| 35 | 99.4705 | 97.4968 | 97.1 | 0.0971 | 199 | 2.25 |
| 40 | 98.2131 | 99.0802 | 5.69 | 0.00569 | 385 | 4.58 |

Note: basis structure of ANN= 48 x HN x 7

3. Conclusion

The main outcome of this research is the design a pattern recognition scheme for identifying UV based on CCPs with incomplete samples. A case study in HDD component manufacturing shows a specific cause and effect relationship between UV and CCP in monitoring quality defects such as tool bluntness, loading error, offsetting tool, and inconsistent pressure. An incomplete sample can be predicted using SMA method before it is recognized using an ANN recognizer. The pattern recognition scheme results gave a highest recognition accuracy at HLN = 35. For future study, it can be observed that various investigations can be made in terms of forecasting technique, recognizer model, and the whole framework of pattern recognition scheme.

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