Bivariate SPC Chart Pattern Recognition Using Modular-Neural Network

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Abstract. In statistical process control (SPC), monitoring and identifying unnatural variation in manufacturing process is challenging when dealing with two correlated quality variables (bivariate). The conventional multivariate SPC charts were designed only for triggering unnatural variation but it is not provide information towards diagnosis. In recent years, several SPC chart pattern recognition schemes were proposed to provide information towards diagnosis based on various category of unnatural variation. In this paper, the modular neural-network scheme was developed to identify nine category of bivariate SPC chart patterns. The success factor for the scheme is outlined as a new perspective in realizing accurate monitoring-diagnosis in quality control.

1. Introduction

The advances in manufacturing technology and manufacturing systems involve processing method, material handling, and quality control. In quality control, selection for an effective statistical process control (SPC) scheme for monitoring and identifying unnatural variation is challenging when dealing with two correlated quality variables (bivariate). In monitoring aspect, the selected scheme should be capable to identify process condition whether in statistically in-control or out-of-control with minimum false alarm. In diagnosis aspect, the selected scheme should be capable to correctly identify the types of out-of-control condition.

The conventional multivariate SPC charts such as Chi-square, multivariate cumulative sum (MCUSUM), and multivariate exponentially weighted moving average (MEWMA) were designed based on monitoring approach to detect the presence of unnatural variation and it were constantly being improved to be more sensitive for triggering small shifts.

Later, the capability of diagnosis was improved through pattern recognition method. An early study on pattern recognition scheme using neural network (NN) recognizer was reported in 2003 [1]. NN is a massive parallel-distributed processor that is capable to learn, recall, and generate knowledge [2]. The properties that are required to recognize and classify the data are often contaminated with noise, unknown distribution and incomplete [3-4]. The other attributes for properties and capabilities to NN in pattern recognition is a non-linearity, input and output mapping, adaptability and fault tolerance, among other. One of the advantages using NN, it can control the noisy measurement and require the
assumption of statistical distribution in monitored data [5]. Based on supervised learning approach, NN shows the ability to recognize and classify patterns directly using identified series of process data streams.

In the related study, many reported researches focused on monitoring and diagnosis of bivariate process mean and/or variance using NN [6-7]. NN has been successfully utilized as a pattern recognizer in classifying unnatural patterns and in estimating the shifts of quality variables [8]. NN training required sufficient data, typically in a large amount that is quite difficult to obtain from real manufacturing process. In most cases, synthetic SPC samples were model and simulated mathematically [9]. Several key success factors have been suggested in the reported researches such as the design of neural network structure, selection of training algorithms, training strategy, and design of input data representation, among others [10].

2. Framework of modular neural-network
The design of modular neural-network scheme consists of four phases as shown in Figure 1.

Phase I: Problem Identification
- Classification for bivariate SPC chart patterns. The process variation can be divided to nine categories as follows: Normal (N00), US01, DS01, US10, DS10, US11, DS11, USDS and DSUS. Symbols U and D respectively represent upward shifts and downward shifts. US10 shows there is upward shifts at the first quality variable (V1), while the second quality variable (V2) is remain at in-control condition. On the other hand, US01 shows there is upward shift at V2, while V1 is remain at in-control condition. In other case, US11 shows there are upward shift at both quality variables (V1, V2).
- The desired of target vector. In this research, the size of input vector was five (5) corresponding for shift. The number of output nodes in this research was set corresponding to the number of pattern classed.

Phase II: Recognizer and input representation, Training and Pre-Testing
- Design of pattern recognizer. A modular-NN recognizer with the multi-layer perceptron’s (MLP) model was designed as shown in Figure 3 and Figure 4. The MLP model was applied since it has been proven effective for classification tasks [11].
- Design of input representation. In many cases, input representation for NN was utilized in the form of raw data or original SPC samples [12-14], features-based such as shape features or statistical feature [15-16] and the combination between raw data and features-based [17]. In this paper, a new statistical features set was selected using design of experiments analysis.
- Training and Testing. Target performance for training was determined at $\geq 95\%$ for normal and shifts patterns.

Phase III: Validation test
The monitoring and diagnosis capability of the scheme can be judged based on the detection speed, rate of false alarm, and the classification accuracy.
**Figure 1.** Process flow in designing the modular-NN scheme [18]

**Figure 2.** Conceptual diagram for the modular-NN scheme
The operating procedure of the modular-NN scheme is represented in Figure 2. In practice, input samples or standardized samples will be taken from real SPC samples. In this paper, simulated data in the form of dynamic SPC samples were used for analysis. The data start from in-control (normal) process and it was changing gradually to out-of-control (shift) process. In order to obtain effective decision in QC, the expected outcome of the pattern recognizer is that it should be able to detect an out-of-control process as fast as possible with minimum false alarm.

Figure 3 shows the model of modular-NN recognizer. It consists of a generalized-MLP and four specialized-MLP model. The generalized-MLP model functions to classify patterns based on five categories, i.e., normal, shifts at first variable (US1), shifts at variable 2 (DS1), shifts at both variables (UD1) and shift at opposite direction (DSU). The specialized-MLP functions to classify patterns based on two categories as follows: US1 to classify US10 and DS10 patterns, DS1 to classify US01 and DS01 patterns, UD1 to classify US11 and DS11 patterns, and DSU to classify USDS and DSUS patterns.

### 3. Results and Discussion

The monitoring and diagnosis performances of the proposed scheme were evaluated based on average run length (ARL\textsubscript{1}) and recognition accuracy percentage (RA) as shown Table 1. The performance results involve various ranges of correlation as follow:

- US10, US01, DS10 and DS01 – correlation between two variables are low (0.1 to 0.3)
- US11 and DS11 – positive and high (0.5 to 0.7)
- For USDS and DSUS – negative and high (-0.7 to -0.5)

The results were represented by average ARL\textsubscript{1} and RA for different class of shifts pattern. In monitoring aspect, it can be observed that the smaller the mean shift, the longer the ARL\textsubscript{1}. Based on this trend, it can be concluded that an out-of-control process with small variation would be more difficult to be detected due to its similarity to an in-control process. In opposite, it would be easy to detect an out-of-control process with large variation due to its difference to an in-control process.

In diagnosis aspect, it can be observed that the stronger the correlation between two variables, the higher the RA. Inversely, size of mean shifts does not change the values of RA. Based on this finding, it can be concluded that an unnatural variation of weak correlation condition would be more difficult to be classified due to mixed properties between in-control and out-of-control process. In opposite, an
unnatural variation with strong correlation would be easy to be classified due to clear properties of out-of-control process.

Table 1. Testing results of modular-NN scheme

| Mean Shift (std dev) | ARL$_1$ and RA | US10, US01, DS10, DS01 | US11, DS11 | USDS, DSUS |
|---------------------|----------------|-------------------------|------------|------------|
| 1.0                 | ARL$_1$        | 10.55 / 10.42           | 7.94 / 8.58| 8.12 / 8.68|
|                     | RA             | 90.6 / 91.2             | 95.6 / 98.2| 90.8 / 96.2|
| 1.5                 | ARL$_1$        | 5.91 / 5.72             | 4.91 / 5.25| 5.04 / 5.20|
|                     | RA             | 92.7 / 91.4             | 99.2 / 99.8| 96.8 / 98.6|
| 2.0                 | ARL$_1$        | 4.35 / 4.18             | 3.63 / 3.77| 3.66 / 3.78|
|                     | RA             | 93.0 / 91.6             | 99.7 / 99.6| 98.4 / 99.3|
| 2.5                 | ARL$_1$        | 3.47 / 3.33             | 2.90 / 3.04| 2.94 / 3.08|
|                     | RA             | 91.6 / 91.6             | 99.2 / 98.8| 98.3 / 98.3|
| 3.0                 | ARL$_1$        | 2.91 / 2.81             | 2.47 / 2.65| 2.45 / 2.60|
|                     | RA             | 89.8 / 89.2             | 99.1 / 99.2| 98.8 / 99.1|

4. Conclusion
Proper design of NN recognizer is important in the development of pattern recognition scheme. In this study, it has become more challenging to monitor and diagnose nine categories of bivariate SPC chart patterns with fast detection and high accuracy. This aim can be realized using a modular – NN recognizer. The utilization of smaller structure of a generalized-MLP and several specialized-MLP was able to achieve efficient recognition. As a result, this finding will be useful to improve quality in manufacturing.

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5
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