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Control Chart Pattern Recognition Using Small Window Size for Identifying Bivariate Process Mean Shifts

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Abstract: There are many traits in the manufacturing technology to assure the quality of products. One of the current practices aims for monitoring the in-process quality of small-lot production using Statistical Process Control (SPC), which requires small samples or small window sizes. In this study, the recognition performance of bivariate SPC pattern recognition scheme was investigated when dealing with small window sizes (less than 24). The framework of the scheme was constructed using an artificial neural network recognizer. The simulated SPC samples in different window sizes (8 ~ 24) and different change points (fixed and varies) were generated to study the recognition performance of the scheme based on mean square error (MSE) and classification accuracy (CA) measures. Two main findings have been suggested: (i) the scheme was superior when recognizing shift patterns with various change points compared to the shift patterns with fixed change point, with lower MSE and higher CA results, (ii) the scheme was more difficult to recognize smaller window size patterns with increasing MSE and decreasing CA trends, since these patterns provided insufficient information of unnatural variation. The outcome of this study would be helpful for industrial practitioners towards applying SPC for small-lot-production.

Keywords: Statistical process control, bivariate process, pattern recognition

1. Introduction

In Just-in-Time practice, applying small lot production is beneficial for achieving a smooth production line, lower inspection and rework cost compared to the large lot size. In the related study of the manufacturing industry, it is well known that manufacturing process variation is a major source of poor-quality products. As such, monitoring and diagnosis of variation is essential towards continuous quality improvement. This becomes more challenging when two correlated variables (bivariate) are involved, whereby selection of statistical process control (SPC) scheme becomes more critical. In recent decades, control chart pattern recognition technique has been studied for identifying the source of unnatural variation in the manufacturing process. Existing studies focus on large-lot production, which involve large window sizes (ws) of 24 ~ 40 (Hassan et. al, 2003; Yu & Xi, 2009; Salehi et. al, 2012; Masood & Hassan, 2013). Inversely, there is less reported work that focuses on small-lot production, which involves smaller ws. Therefore, this study aims to investigate the performance trends of the SPC scheme when dealing with bivariate process and small ws, for instance, less than 24 samples.

2. SPC Pattern Recognition

El-Midany et al. (2010) note that an artificial neural network (ANN) can be performed to the SPC chart analysis using two general approaches: (i) neural networks to detect deviation in mean shifts and/or variance shifts; (ii) neural network to identify unnatural variation based on abnormal patterns of control charts.

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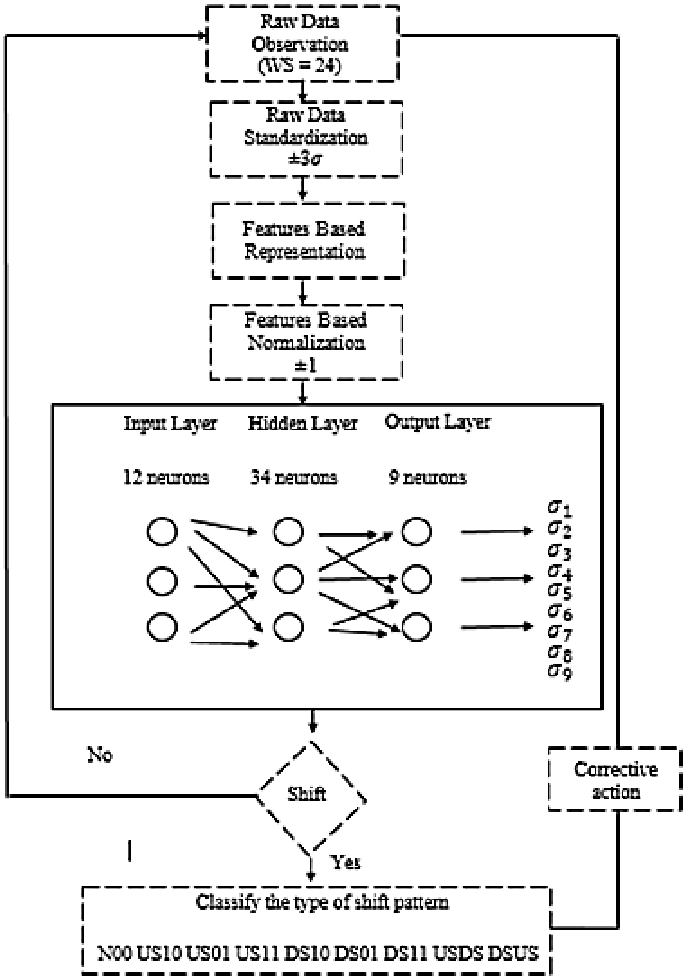

Fig. 1 - Control chart pattern recognition scheme

Based on Figure 1, the simulation process starts with input of raw data-based observation (inspection) samples at window size 24. Then, the actual observation samples are standardized to the range of (-3, +3). The next step is data transformation to be feature-based input representation and normalization within a range of ±1. The normalized data are processed using artificial neural network (ANN) to recognize and classify based on 9 pattern categories. In order to achieve a high recognition performance, proper selection of feature-based data representation and ANN setting are crucial.

3. Results and Discussion

3.1 Recognition Performance Based on Mean Square Error

Figure 2 shows the mean square error (MSE) results for different number of samples (window size-ws) within a range of 2 ~ 24. The MSE Fixed represents the shift patterns with fixed change point, while MSE Varies represents the shift patterns with various change points.

There are two main findings: (i) for both types of shift patterns, the MSE value increased when the window size got shorter, and (ii) the MSE values for various change point patterns are lower than the fixed change point pattern. The first finding clearly indicated that the shift patterns with less data information were more difficult to be recognized especially to distinguish between normal and shift information. On the other hand, the second finding showed that various change point patterns can improve data properties to distinguish between normal and shift patterns.

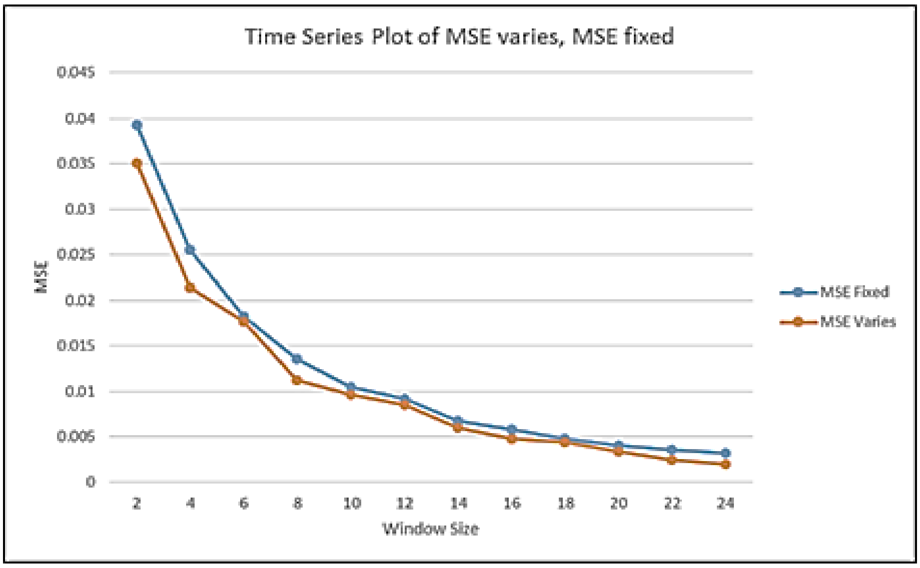

Fig. 2 - MSE value for different window size patterns

The recognition performance based on MSE value has been significantly proven based on statistical test, paired T-test. For the second finding, the MSE values for various change point patterns were consistently lower at all window sizes. This can be referred to the mean (0.01062 vs 0.01202, difference 0.001397) and P (0.006) values as summarized in Table 1. The P = 0.006 (< 0.05) proved that the mean MSE values for both methods were not equal.

Table 1 - Paired T-test and CI: MSE fixed and MSE varies

	N	Mean	St. Dev	SE Mean
Fixed	12	0.012020	0.0109200	0.003150
Varies	12	0.010620	0.0097600	0.002820
Difference	12	0.001397	0.0001438	0.000415

95% CI for mean difference: (0.750, 2.720)

T-Test of mean difference = 0 (vs not = 0): T-Value = 3.88, P-Value = 0.006

3.2 Recognition Performance Based on Classification Accuracy

Figure 3 shows the Classification Accuracy (CA) results for different number of samples (window size -ws), i.e. within a range of 2 ~ 24. The Accuracy Fixed represents the shift patterns with fixed change point, while Accuracy Varies represents the shift patterns with various change points.

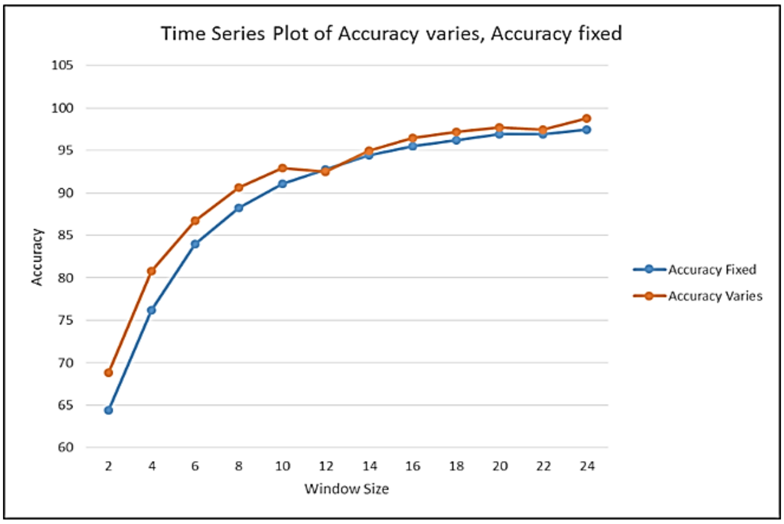

Fig. 3 - Classification accuracy for different window size patterns

There are other two main findings: (i) for both types of shift patterns, the CA decreased when the window size got shorter, and (ii) the CA for various change point patterns were higher than the fixed change point patterns. Both results clearly presented that the CA was opposite the MSE value, which is theoretically acceptable. The first finding clearly described that the shift patterns with less data information were more difficult to be recognized especially to distinguish between normal and shift information. On the other hand, the second finding showed that various change point patterns can improve data properties to distinguish between normal and shift patterns.

The recognition performance based on CA has also been significantly proven based on statistical test, paired T-test. For the second finding, the CA for various change point patterns was consistently higher at all window sizes. This can be referred to the mean (91.25% vs 89.51%, difference 1.73%) and P (0.006) values as summarized in Table 2. The P = 0.006 (< 0.05) proved the mean CA for both methods was not equal.

Table 2 - Paired T-test and CI: accuracy fixed and accuracy varies

	N	Mean	St. Dev	SE Mean
Fixed	12	91.25	8.79	2.54
Varies	12	89.51	10.13	2.92
Difference	12	1.730	1.540	0.445

95% CI for mean difference: (0.750, 2.720)

T-Test of mean difference = 0 (vs not = 0): T-Value = 3.88, P-Value = 0.006

The numerical results of MSE and CA are summarized in Table 3 as follows:

Table 3 - Summary of MSE value and CA

Fixed Change Point			Varies Change Points		
WS	MSE	CA (%)	WS	MSE	CA (%)
24	0.00319	97.41	24	0.00191	98.73
22	0.0035	96.90	22	0.00243	97.43
20	0.00399	96.95	20	0.00435	97.10
18	0.00476	96.23	18	0.00439	96.21
16	0.00575	95.53	16	0.00473	95.49
14	0.00671	94.43	14	0.00602	94.97
12	0.00918	92.78	12	0.00852	92.50
10	0.0105	91.10	10	0.00967	92.95
8	0.0136	88.26	8	0.0112	90.59
6	0.0182	84.03	6	0.0177	86.75
4	0.0255	76.17	4	0.0214	80.82
2	0.0393	64.45	2	0.0351	68.84

Figure 4 presents the recognition performance based on CA for each category of shift patterns. The results were taken for various change point patterns, since they gave higher performance compared to fixed change point pattern.

The CA outcomes were justified based on strength of unnatural variation information: (i) patterns with shifts at one variable only, and (ii) patterns with shifts at both variables. Shift patterns in category (i) involving US10, US01, DS10 and DS01 gave lower CA compared to category (ii) involving US11, DS11, USDS and DSUS.

It can be concluded that shift patterns in category (i) were more difficult to be recognized, since it provided insufficient information of unnatural variation, such as shifts at one variable only. Inversely, shift patterns in category (ii) were easily recognized, since it provided enough information of unnatural variation at both variables.

Based on the authors' point of view, this weakness could be solved by improving the strength of unnatural variation information. This is the need for further research.

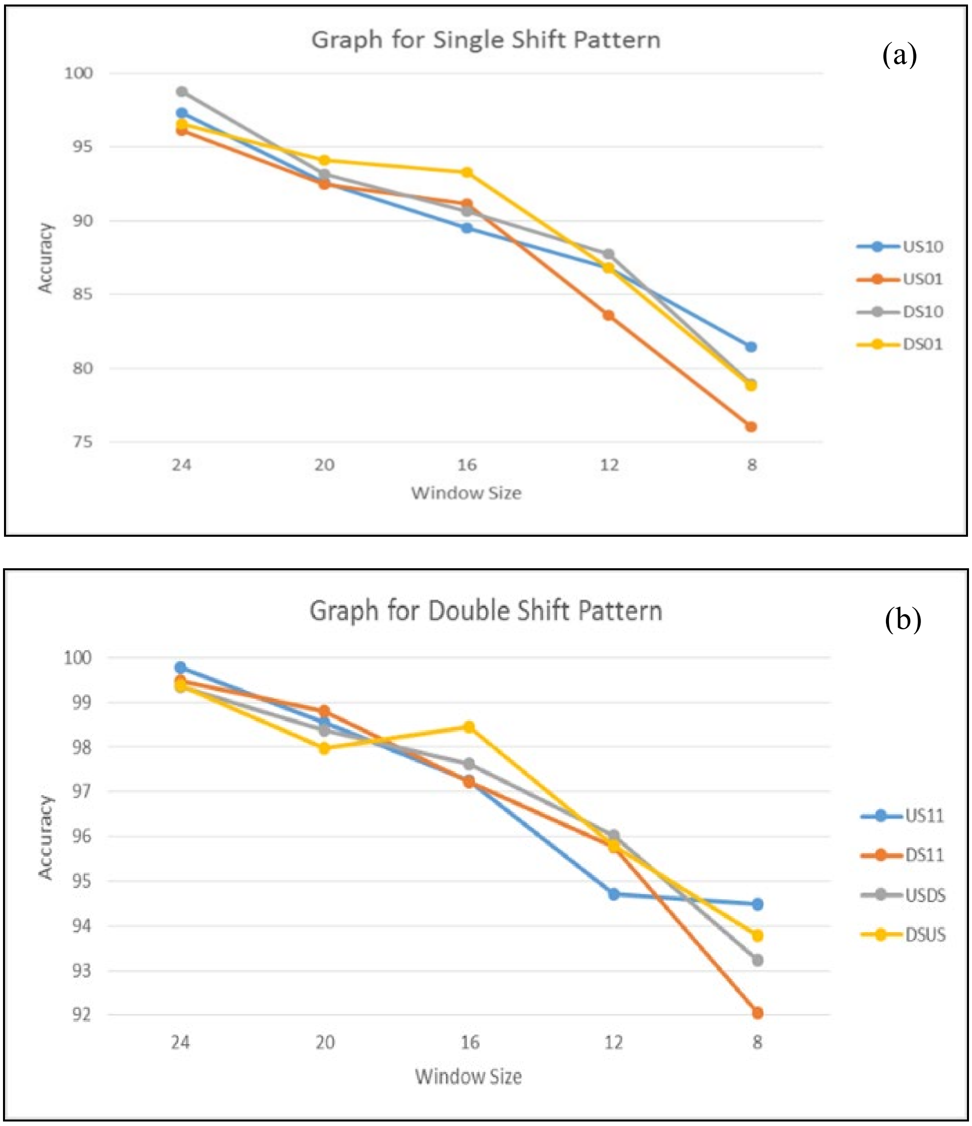

Fig. 4 - Classification accuracy for individual shifts patterns with varies change point (a) Shift patterns based on unnatural variation at one variable only (b) Shift patterns based on unnatural variation at both variables

4. Conclusion

In dealing with bivariate SPC and small window size samples, the control chart pattern recognition scheme using an ANN is successfully constructed to classify the unnatural variation. There are two main findings that can be proposed: (i) the scheme is superior when recognizing shift patterns with various change points compared to the shift patterns with fixed change point. With lower MSE and higher CA results, (ii) the scheme is more difficult to recognize the smaller window size patterns with an increasing MSE and decreasing CA trends, since these patterns provide insufficient information of unnatural variation.

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