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Recognition of Concurrent Control Chart Patterns in Auto-correlated Processes Using Support Vector Machine

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Abstract

Control chart pattern recognition (CCPR) is an important issue in statistical process control because unnatural control chart patterns (CCPs) exhibited on control charts can be associated with specific causes that adversely affect the manufacturing processes. In recent years, many machine learning techniques have been successfully applied to CCPR. However, such existing research for CCPR has mostly been developed for identification of basic CCPs (Shift Patterns, Trend Patterns, Cyclic Pattern and Systematic Pattern). Little attention has been given to the identification of concurrent CCPs (two or more basic CCPs occurring simultaneously) which are commonly encountered in practical manufacturing processes. In addition, these existing researches also assume the process data are independently and identically distributed which may not be appropriate for certain manufacturing processes. This study proposes a support vector machine (SVM) approach to identify concurrent CCPs for a multivariate process with autocorrelated observations which can be characterized by a first order autoregressive (AR(1)) model. The numerical results indicate that the proposed model can effectively identify two concurrent identical CCPs but for those cases involving one trend pattern and one shift pattern, their recognition accuracy deteriorates to around 20% to 50% depending on the autocorrelation coefficients used in the data model.

Keywords: control chart pattern, support vector machine, autocorrelation process

1. Introduction

The effectiveness of the use of control charts depends on the ability to recognize patterns. The common types of CCP exhibited on statistical process control charts have been formalized in early literature. In most literature, the following seven typical types of basic CCP, i.e., Upward and Downward Shift Pattern (USP and DSP); Upward and Downward Trend Pattern (UTPand DTP); Cyclic Pattern (CP); Systematic Pattern (SP); Natural Pattern (NP), are usually addressed. Identification of unnatural patterns canfacilitate early detection of an out-of-control process and the diagnostic search process by narrowing down the set of possiblecauses that must be investigated. For instance, shift patterns mayindicate changes in material, machine or operator, while trend patternsmay indicate tool wear. Cyclic patterns may indicate voltage fluctuation in power supply [1-3].

There is a crucial need for an automatic and effective analysis and interpretation methodology for control chart pattern recognition (CCPR), which enables indication of the real state of the manufacturing process. CCPR studies consist of the description, the identification, the explicit classification, and the extraction of patterns in data.

In recent years, many machine learning techniques have been successfully applied to CCPR. However, such existing research for CCPR has mostly been developed for identification of basic CCPs (Shift Patterns, Trend Patterns, Cyclic Pattern and Systematic Pattern). Little attention has been given to the identification of concurrent CCPs (two or more basic CCPs occurring simultaneously) which are commonly encountered in practical manufacturing processes. In addition, these existing researches also assume the process data are independently and identically distributed which may not be appropriate for certain manufacturing processes. For those processes involving continuous manufacturing operations (including the manufacture of food, chemicals, and paper

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and wood products), the consecutive observations of product characteristics are often highly correlated.

The purpose of this paper is to propose a support vector machine (SVM) approach to identify concurrent CCPs for a multivariate process with autocorrelated observations.

2. Method

This study uses simulations to generate the required sets of CCP examples for training, testing, and performance evaluation of the proposed model. The mathematical expressions for CCP generation are expressed in a general form that consists of process mean, common cause variation and special disturbance from assignable causes. The equations and parameters used to generate the data points are shown in Table 1.

Table 1 CCP equations and parameters

patterns	equations	parameters
Natural pattern	$x_i = \mu + r_i\sigma$	μ=0, σ=1
Trend pattern	$x_i = \mu + r_i\sigma + t \times i$	$t \in \pm[0.10, 0.26]$
Shift pattern	$x_i = \mu + r_i\sigma + u \times s$	$s \in \pm[1.0, 3.0]$ $u = 0$ or 1
Cyclic pattern	$x_i = \mu + r_i\sigma + a \times \sin\frac{2\pi t}{\Omega}$	$a \in [1.0, 3.0]$
Systematic pattern	$x_i = \mu + r_i\sigma + d(-1)^i$	$d \in [1.0, 3.0]$

The following equations are used to simulate the autocorrelated data.

$$X_{1t} = \mu_1 + \phi_{11}X_{1,t-1} + \phi_{12}X_{2,t-1} + \varepsilon_{1t} \tag{1}$$

$$X_{2t} = \mu_2 + \phi_{21}X_{1,t-1} + \phi_{22}X_{2,t-1} + \varepsilon_{2t} \tag{2}$$

where ϕ_{ij} are autocorrelated coefficients, and ϕ_{11}= {1.0, 0.7 0.4, 0.1}, ϕ_{22}= {1.0, 0.7, 0.4, 0.1}.

For training and testing the concurrent patterns, a SVM based on radial basis kernel function is chosen inthis study. Related parameters C and γ for this kernel were varied in the fixed ranges [2-5, 25]. Using the simulated training and testing examples, the optimal (C, γ) was determined as [1, 0.03]. The observation window sizes of 24 and 32 are selected according to the suggestions by Guh and Tannock [4] and Hachicha and Ghorbel [1].

3. Results and Discussion

The concurrent CCPs were a combination of any two of the basic unnatural CCPs. Thus, 13 types of concurrent CCP, namely USP mixed with UTP (USP+UTP), USP mixed with DTP (USP+DTP), USP mixed with CP (USP+CP), USP mixed with SP (USP+SP), DSP mixed with UTP (DSP+UTP), DSP mixed with DTP (DSP+DTP), DSP mixed with CP (DSP+CP), DSP mixed with SP (DSP+SP), UTP mixed with CP (UTP+CP), UTP mixed with SP (UTP+SP), DTP mixed with CP (DTP+CP), DTP mixed with SP (DTP+SP), CP mixed with SP (CP+SP) are addressed in this study.

Table 2 Accuracy of CCPR

pattern	(ϕ_1, ϕ_2)					
	1.0/.7	1.0/.4	1.0/.1	.7/.7	.7/.4	.7/.1
NP	100.0	100.0	100.0	100.0	100.0	100.0
UTP	69.71	81.24	89.76	80.71	88.88	95.47
DTP	72.53	83.41	96.00	81.71	89.24	99.41
USP	95.59	97.59	99.71	97.94	99.88	99.94
DSP	98.76	99.41	99.47	99.35	99.53	100.0
CP	96.94	99.24	100.0	99.29	99.65	100.0
SP	98.06	99.71	100.0	99.47	99.88	100.0
UTP+USP	27.99	26.85	22.79	28.25	27.44	24.09
UTP+DSP	32.64	32.89	35.81	35.44	35.11	36.24
UTP+CP	97.96	98.81	99.48	98.92	99.46	99.73
UTP+ SP	35.56	38.54	40.34	33.65	36.16	39.68
DTP+USP	44.35	46.34	46.33	45.56	47.52	48.18
DTP+DSP	22.19	22.38	23.35	22.49	23.99	24.99
DTP+CP	97.96	98.92	99.73	98.98	99.56	99.95
DTP+ SP	30.56	30.21	32.13	28.92	28.07	28.65
USP+ CP	99.44	99.78	99.94	99.76	99.88	99.99
USP+ SP	99.78	99.99	100.00	99.91	100.00	100.0
DSP+ CP	99.84	99.98	100.00	99.95	99.99	100.0
DSP+ SP	99.87	99.94	100.00	99.96	99.99	100.0
CP+SP	98.95	99.42	99.81	99.36	99.53	99.92
Accura-cy	75.93	77.73	79.23	77.48	78.69	79.81

Simulation results in Table 2 show that the rate of accuracy for patterns of UTP, DTP, UTP+USP, UTP+DSP, UTP+SP, DTP+USP, DTP+DSP, DTP+SP is worse than the other patterns. It is noticed that if the trend pattern was mixed with other patterns, their recognition performance would decrease.

4. Conclusions

In this paper, a support vector machine approach is proposed to identify concurrent CCPs for a multivariate process with autocorrelated observations which can be characterized by afirst order autoregressive (AR (1)) model. The numerical results indicate that the proposed model can effectively identify two concurrent identical CCPs but for those cases involving one trend pattern and one shift pattern, their recognition accuracy deteriorates to around 20% to 50% depending on the autocorrelation coefficients used in the data model.

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References

[1] W. Hachicha and A. Ghorbel, "A survey of control-chart pattern-recognition literature (1991–2010) based on a new conceptual classification scheme," Computers & Industrial Engineering, vol. 63, no. 1, pp.204-222, 2012.

[2] L.J. Xie, N. Gu, D.L. Li, and Z.Q. Cao, "Concurrent control chart patterns recognition with singular spectrum analysis and support vector machine," Computers & Industrial Engineering, vol. 64, no. 1, pp. 280-289, 2013.

[3] W. A. Yang, W. Zhou, W. Liao, and Y. Guo, "Identification and quantification of concurrent control chart patterns using extreme-point symmetric mode decomposition and extreme learning machines," Neurocomputing, vol. 147, pp. 260-270, 2015.

[4] R. S. Guhand J. Tannock, "Recognition of control chart concurrent patterns using a neural network approach,"International Journal of Production Research, vol. 37, no.8, pp.1743-1765, 1999.