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On line detection of mean and variance shift using neural networks and support vector machine in multivariate processes

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ABSTRACT

The effective recognition of unnatural control chart patterns (CCPs) is one of the most important tools to identify process problems. In multivariate process control, the main problem of multivariate quality control charts is that they can detect an out of control event but do not directly determine which variable or group of variables has caused the out of control signal and how much is the magnitude of out of control. Recently machine learning techniques, such as artificial neural networks (ANNs), have been widely used in the research field of CCP recognition. This study presents a modular model for on-line analysis of out of control signals in multivariate processes. This model consists of two modules. In the first module using a support vector machine (SVM)-classifier, mean shift and variance shift can be recognized. Then in the second module, using two special neural networks for mean and variance, it can be recognized magnitude of shift for each variable simultaneously. Through evaluation and comparison, our research results show that the proposed modular performs substantially better than the traditional corresponding control charts. The main contributions of this work are recognizing the type of unnatural pattern and classifying the magnitude of shift for mean and variance in each variable simultaneously.

1. Introduction

In many industrial processes, statistical process control (SPC) techniques are some of the most frequently used tools for improving quality. Control charts are the most widely applied SPC tools used to reveal abnormal variations of the monitored measurements. In addition, the rapid growth of the automatic data acquisition system for process monitoring has led to the increased interest in the simultaneous scrutiny of several interrelated quality variables. These techniques are often referred as multivariate SPC (MSPC) procedures. The main problem of multivariate quality control charts is that they can detect an out of control event but do not directly determine which variable or group of variables has caused the out of control signal and how much is the magnitude of out of control. Incorporating pattern recognition in the control charting scheme can address this problem. With a certain control chart pattern, the diagnosis search can be shortened if one has knowledge of the CCP type (e.g., a shift or a trend) and corresponding knowledge of which process factors could cause these CCPs. Therefore, timely recognition of CCPs is a crucial task in SPC for determining the potential assignable causes [1].

To clarify the main problem, let $X_{ij} = (X_{ij1}, X_{ij2}, \ldots, X_{ijp})$ be a p dimension vector that represents the p quality characteristics in the jth observation of the ith subgroup (sample), where i = 1,2,... and j = 1,2,...,n. The lth component of X_{ij}, X_{ijl} denotes the lth quality characteristic, l = 1,2,...,p. A standard multivariate quality control problem is to determine whether an observed vector of measurements $X_{ij} = (X_{ij1}, X_{ij2}, \ldots, X_{ijp})$, a p-component vector, from a particular sample exhibits any evidence of a location shift from a set of satisfactory mean values. It is assumed that *Xij*'s are independent and have identically a multivariate normal distribution with the known mean μ and covariance matrix Σ when the process is in control. Let $\bar{X}_i$ represent the mean vector for the ith subgroup. The statistic plotted on a multivariate χ^2 control chart for the ith subgroup is given by,

$$\chi_i^2 = n(\bar{X}_i - \mu)\Sigma^{-1}(\bar{X}_i - \mu) \tag{1}$$

when the process is in control, it follows a χ^2 central distribution with p degrees of freedom. Therefore, a multivariate χ^2 control chart can be constructed by plotting χ_i^2 versus time with an upper control limit (UCL) given by $\chi^2_{\alpha,p}$ where α is an appropriate significance level for performing the test.

Specific patterns of mean and variance charts can be associated independently with different problems when relevant process

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knowledge is accessible. Therefore, the simultaneous recognition and analysis of mean and variance CCPs is very helpful in the diagnostic search for an out of control process. Most of the researches in SPC have been focused on controlling of means. However, monitoring of process variability will be desirable. Alt [2] presented a control method based on a sample generalized variance, denoted by $|S|$ and uses the mean and variance of $|S|$. For a given sample size n, the upper control limit, centerline and lower control limit of the control chart for $|S|$ would be:

$$\begin{aligned} UCL &= \left|\Sigma_0\right| (b_1 + 3\sqrt{b_2}) \\ CL &= b_1 \left|\Sigma_0\right| \\ UCL &= \left|\Sigma_0\right| (b_1 - 3\sqrt{b_2}) \end{aligned} \tag{2}$$

where $\left|\Sigma_0\right|$ is the determinant of the in-control covariance matrix. The coefficients b_1 and b_2 are computed as:

$$\begin{aligned} b_1 &= \frac{1}{(n-1)^p} \prod_{i=1}^{p} (n-i) \\ b_2 &= \frac{1}{(n-1)^{2p}} \prod_{i=1}^{p} (n-i) \left(\prod_{j=1}^{p} (n-j+2) - \prod_{j=1}^{p} (n-j) \right) \end{aligned} \tag{3}$$

If the calculated value for lower control limit is less than zero, it is replaced with zero. Usually Σ will be estimated by a sample covariance matrix S, based on the analysis of preliminary samples. In this case, Σ must be replaced by $|S|/b_1$.

Control charts do not provide any pattern-related information when the process is out of control. Many supplementary rules, like zone tests or run rules and expert systems have also been implemented in control chart pattern recognition (CCPR). But according to the reported works, the overall percentages of correctly recognized for these approaches is low. Recently, many studies used artificial neural networks (ANNs) in order to detect patterns more effectively than the conventional approach and their aim is the automatic diagnosis of the patterns. Neural networks (NNs) have excellent noise tolerance in real time, requiring no hypothesis on statistical distribution of monitored measurements. This important feature makes NNs promising and effective tools that can be implemented to improve data analysis in manufacturing quality control applications. In addition, in recognition problems, NNs can recall learned patterns from noisy representations. This feature makes NNs highly appropriate for CCPR because unnatural CCPs are generally contaminated by natural variations in the process. Such applications have been reported to outperform the conventional methods in terms of recognition accuracy and speed. Development of NNs in CCPR is briefly reviewed as follows.

Artificial neural networks have been successfully applied to univariate statistical process control. The reader can refer to Zorriassatine and Tannock [3] that reviews of the applications of neural networks for univariate process monitoring. Recently, many researchers have investigated the application of artificial neural networks to multivariate statistical process control. In many quality control settings, the process may have two or more correlated variables. To control this process, the usual practice has been to maintain a separate (univariate) chart for each characteristic. Unfortunately, this could result in some fault out of control alarms when the characteristics are highly correlated. Zorriassatine et al. [4] applied a neural network classification technique known as novelty detection to monitor bivariate process mean and variance. Chen and Wang [5] developed an artificial neural network-based model for identifying the characteristic or group of characteristics that cause the signal and for classifying the magnitude of the mean shifts. Niaki and Abbasi [6] developed a special two levels-based model using T^2 control chart for detecting the out of control signals and a multi layer perceptron neural network for identifying the source(s) of the out of control signals. A similar study can be found in Aparisi et al. [7] They evaluated the correct classification percentage, and showed that the neural network is better than traditional decomposition method. Later, Aparisi et al. [8] designed a neural the network to interpret the out of control signal of the MEWMA chart. Guh and Shiue [9] proposed a straightforward and effective model to detect the mean shifts in multivariate control charts using decision tree learning techniques. Experimental results using simulation showed that the proposed model could not only efficiently detect the mean shifts but also accurately identify the variables that have deviated from their original means. Yu and Xi [10] presented a learning-based model for monitoring and diagnosing out of control signals in a bivariate process. In their model, a selective neural network ensemble approach was developed for performing these tasks. El-Midany et al. [11] proposed a framework for multivariate process control chart recognition. The proposed methodology uses the artificial neural networks to recognize a set of subclasses of multivariate abnormal patterns, identify the responsible variable(s) on the occurrence of abnormal pattern and classify the abnormal pattern parameters.

In the most presented approaches, recognition problem is limited to identifying the characteristic or group of characteristics that cause the unnatural pattern, but this study proposes a new approach that can identify unnatural patterns (mean shift and variance shift) for each quality variables simultaneously and identify the magnitude of shift for each deviated quality variable. In addition, most of previous works focused on mean shift, but the application of neural network to monitoring variability of multivariate processes is limited. Low et al. [12] presented a neural network procedure for detecting variance shifts in a bivariate process. They indicated that neural networks have better performance than the traditional multivariate chart according to the average run length. In their approach the performance of neural network is dependent on the covariance matrix as well as the patterns of shifts in the covariance matrix. Zorriassatine et al. [4] used neural networks to detect a proportional changes in all elements of covariance matrix. They evaluated classification accuracy for bivariate processes. Cheng and Cheng [13] considered two classifiers based on neural network and support vector machine to identify the source of variance shifts in the multivariate process. In their approach, after detection a variance shift by the generalized variance $|S|$ chart, a classifier will determine which variable is responsible for the variance shift.

Most previous works consider variance shift and mean shift for a multivariate process separately or they consider these unnatural patterns simultaneously only for univariate processes. In addition, few works that consider the recognition problem of multi-unnatural patterns for multivariate process, do not obtain any information about magnitude of deviations. This information can help quality participators for rapid recognition of unnatural pattern roots. Type of unnatural patterns and magnitude of shift in a variance shift or a mean shift will be recognized for each variable by the proposed model simultaneously.

In this paper proposes a model that consists of two modules. In the first module using a support vector machine-classifier, type of unnatural pattern can be recognized. Then using two special-neural networks for shift mean and variance shift, it can be recognized the magnitude of shift for each quality variable simultaneously. The statistical performance of model will be compared with other competing multivariate process mean and variability control schemes.

The rest of this research is organized as follows. Section 2 describes the proposed model for solving CCPR problem. Section 3 presents a case study and also the overall performance of model are evaluated and compared to the corresponding multivariate control charts. Conclusions will be presented in Section 4.