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Time-adaptive support vector data description for nonstationary process monitoring

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ABSTRACT

Statistical process control techniques are widely used for quality control to monitor the stability of a process over time. In modern manufacturing systems with complex and variable processes, appropriate control chart techniques that can efficiently address nonnormal processes are required. Furthermore, in real manufacturing environments, process changes occur frequently because of various factors such as product and setpoint changes, catalyst degradation, seasonal variations, and sensor drift. However, conventional control chart schemes cannot necessarily accommodate all possible future conditions of a process because they are formulated based on information recorded in the early stages of the process. Several attempts have been made to accommodate process changes over time. In the present paper, we propose a time-adaptive support vector data description-based control chart that can address not only nonnormal in-control observations, but also time-varying processes. The effectiveness and applicability of the proposed chart was demonstrated through experiments with simulated data and real data from the metal frame process in mobile device manufacturing.

1. Introduction

Statistical process control (SPC) methods are widely used in many industries such as manufacturing and service operations to monitor and improve process performance over time (Woodall et al., 2000). The goal of SPC methods is to reduce predictable quality variations and monitor the complete system to detect unexpected root causes of variation (Ferracuti et al., 2015; Vander Wiel et al., 1992). A control chart is a representative tool of SPC that distinguishes between the inherent variations within the process and variations from unwanted process disruptions (Gitlow, 2009; Oakland, 2008). Control charts are commonly used as graphical tools to quickly detect changes in manufacturing processes (Noorossana et al., 2015; Stoumbos and Sullivan, 2002).

The Shewhart control chart is the most representative SPC chart for manufacturing processes. Shewhart (1939) developed a univariate control chart to monitor a single quality characteristic. However, monitoring these quality characteristics independently can be misleading because modern manufacturing systems involve many inter-correlated quality characteristics (Hwang and Lee, 2015; Lu, 1998).

This limitation prompted the development of multivariate control charts that can simultaneously consider the correlations between multiple quality characteristics and effectively manage the overall probability of Type I errors. Hotelling's T^2 control chart has been widely used to monitor multivariate processes. The monitoring statistics for the T^2 chart are computed from the following equation:

$$T^2 = \left(x - \bar{x}\right)^T S^{-1} \left(\mathrm{x} - \bar{\mathrm{x}}\right), \tag{1}$$

where $\bar{x}$ and S are, respectively, the sample mean vector and sample covariance matrix determined from the in-control data. The T^2 statistic can be considered the distance of an observation from the center of in-control observations, while considering the correlation among variables. The control limit of a T^2 chart is proportional to the percentile of an F-distribution assuming that in-control observations follow a multivariate normal distribution (Mason and Young, 2002).

As modern manufacturing processes become more complex, in-control observations of many industrial processes do not follow a normal distribution (Hu et al., 2015; Yang and Arnold, 2013; Gani et al., 2011). Thus, traditional control charts such as T^2 charts do not effectively reflect the quality characteristics of observations that follow the nonnormal distribution. To overcome the shortcomings of conventional control charts under nonnormal situations, a number of methods have been proposed to use one-class classification (OCC) algorithms to monitor nonnormal processes (Liu et al., 2015; Tuerhong et al., 2014; Sukchotrat et al., 2009).

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Both OCC algorithms and control charts assume that only the in-control observations are available for measuring the degree of abnormality of new observations. The novelty scores of OCC algorithms are used as the monitoring statistics of OCC-based control charts. This stream of research began with the introduction of the K chart based on a support vector data description (SVDD) algorithm (Sun and Tsung, 2003). The K charts performed well for nonnormal or unknown distributed in-control processes. Kumar et al. (2006) constructed robust K charts through normalized monitoring statistics and demonstrated that these charts can efficiently handle autocorrelated process data. Ning and Tsung (2013) proposed a guideline to determine the K chart parameters in practice. Gani et al. (2011) provided an assessment of the K chart by applying it to a real industrial process and revealed that the K chart is more sensitive to small mean shifts than the T^2 chart. Khediri et al. (2012) proposed the kernel *k*-means-based SVDD control chart for multimodal processes. Sukchotrat et al. (2009) proposed a bootstrapping strategy to establish robust control limits. In addition to the SVDD algorithm, other OCC control charts include the hybrid novelty score-based control chart and the K^2 chart, based on the *k*-nearest neighbors data description algorithm (Tuerhong et al., 2014; Sukchotrat et al., 2009). In summary, OCC-based control charts have demonstrated their improved performance in many of the nonnormal and nonlinear situations frequently encountered in modern manufacturing systems (Tuerhong and Kim, 2015; Grasso et al., 2015; Kim et al., 2011).

However, in addition to the nonnormal situations, the time-varying operation of process data is also common in modern industrial processes (Haimi et al., 2016; Soares and Araújo, 2015; Ge and Song, 2013). Such behavior can be caused by several factors such as setpoint and throughput changes, catalyst degradation, sensor drift, and the presence of unmeasured disturbances (Ketelaere et al., 2011; Choi et al., 2006). Time-varying process operation is considered a critical issue in many electronic and chemical engineering fields (Li et al., 2000; Qin, 1998). Because conventional SPC schemes are formulated based on the data recorded in the early stage of the process, it is difficult to describe all possible future conditions of a process. Consequently, traditional control charts may detect normal variations as faults in time-varying situations, leading to a high level of Type I error rates (i.e., false alarms). To enhance the monitoring performance and reduce false alarms in time-varying situations, some studies have proposed an adaptive technique in multivariate control charts (Chakour et al., 2015; Ge and Song, 2008; Lee et al., 2006). These approaches are based on updating the parameters of the control charts for time-varying processes.

Time-varying process monitoring methods can be divided into two categories: recursive estimation with a weighting parameter and moving window. In the first category, a weighting parameter is added to the control chart to allow old data to be gradually forgotten. The adaptive principal component analysis (PCA)-based T^2 chart was proposed in which the sample mean and sample covariance of the in-control data can be updated in such a manner that more weight is assigned to current observations than past observations (Zhang et al., 2012; Choi et al., 2006; Li et al., 2000; Wold, 1994). As for an example of the second category, the moving window-based methods exclude the oldest data and include the newest data simultaneously with the data window. The moving window PCA-based T^2 chart was developed to control time-varying processes (Liu et al., 2009; Wang et al., 2005). Xie and Shi (2012) suggested an adaptive form of Gaussian mixture model (GMM) charts using a moving window scheme for time-varying processes. In the moving window GMM, having found the most suitable Gaussian components for the new data, the parameters of the components are updated by a moving window.

Despite these efforts, the majority of time-adaptive control charts rely on the assumption that in-control observations follow a normal distribution. The above-mentioned adaptive PCA-based process monitoring methods used T^2 statistics in the projected space. Thus, a normality assumption of in-control observations in the projected space is necessary. The moving window GMM method also assumes that each group of the mixture follows a Gaussian distribution.

The present study focuses on developing a multivariate control chart for both nonnormal and time-varying processes. The proposed chart is an extension of the existing SVDD-based chart adding a weight factor to effectively address the time-varying situations. We define the updating region for the efficient model-updating structure of the control chart.

The remainder of the paper is organized as follows. Section 2 reviews the existing SVDD-based control charts. Section 3 describes the proposed time-adaptive SVDD-based control chart by emphasizing its adaptive capability for time-varying processes. In Section 4, a simulation study is conducted to examine the performance of the proposed time-adaptive SVDD-based control chart under various scenarios. Section 5 presents the results of a case study using actual data from the metal frame process in mobile device manufacturing exhibiting nonnormal and time-varying characteristics. Section 6 provides concluding remarks.

2. SVDD-based control charts

The SVDD algorithm is one of the representative OCC algorithms (Tax and Duin, 2004). The objective of the SVDD algorithm is to determine a sphere with minimal volume that can envelop all of the data points in the training set $\mathbf{x}_i = [x_{i1}, x_{i2}, \ldots, x_{ip}]^T$, for $i = 1, 2, \ldots, n$. This sphere is characterized by two factors, sphere center $\boldsymbol{a}$ and radius R. That is, the problem is to:

$$min F\left(R, \boldsymbol{a}, \varepsilon_i\right) = R^2 + C\sum_{i=1}^{n}\varepsilon_i, \tag{2}$$

$$\text{s.t. } \left\|\mathbf{x}_i - \boldsymbol{a}\right\|^2 \le R^2 + \varepsilon_i, \quad \varepsilon_i \ge 0, \quad \forall i, \tag{3}$$

where C is the trade-off parameter between the sphere's volume and the misclassification error (also referred to as the regularization parameter), and ε_i is the slack variable that allows $\mathbf{x}_i$ to be outside the sphere.

Eqs. (2) and (3) can be solved by the following Lagrange dual formulation:

$$max \sum_{i=1}^{n}\alpha_i\left(\mathbf{x}_i\cdot\mathbf{x}_i\right) - \sum_{i,j=1}^{n}\alpha_i\alpha_j\left(\mathbf{x}_i\cdot\mathbf{x}_j\right), \tag{4}$$

$$\text{s.t. } \sum_{i=1}^{n}\alpha_i = 1, \quad 0 \le \alpha_i \le C, \quad \forall i, \tag{5}$$

where α_i is Lagrange multiplier. Having solved the above Lagrange formulation, the values of α_i and data point $\mathbf{x}_i$ with $\alpha_i > 0$ are obtained. The data points $\mathbf{x}_i$ are called support vectors.

SVDD algorithms can generate a flexible boundary by employing a kernel trick, which maps an input space into a higher dimensional feature space by replacing the inner product with kernel functions. Although many kernel functions are available, Tax and Duin (1999) demonstrated that the following Gaussian kernel is one of the most effective functions for SVDD.

$$K\left(\mathbf{x}_i\cdot\mathbf{x}_j\right) = \exp\left(-\left\|\mathbf{x}_i - \mathbf{x}_j\right\|^2/s^2\right), \tag{6}$$

where $s \neq 0$ is the width parameter that controls the level of detail of the SVDD boundary. For new observation $\mathbf{z}$, the kernel distance to the center $\boldsymbol{a}$ can be calculated by

$$\|\mathbf{z} - \boldsymbol{a}\|^2 = K(\mathbf{z}\cdot\mathbf{z}) - 2\sum_{i=1}^{n}\alpha_i K\left(\mathbf{z}\cdot\mathbf{x}_i\right) + \sum_{i,j=1}^{n}\alpha_i\alpha_j K(\mathbf{x}_i\cdot\mathbf{x}_j). \tag{7}$$

For classification, testing observation $\mathbf{z}$ is classified as the target when this distance is less than or equal to R^2.

Several studies have implemented the SVDD algorithm to solve SPC problems. However, previous studies have not addressed time-varying situations. This motivates the focus of this paper on the development of an SVDD-based control chart to handle time-varying and nonnormal situations.