Expert Systems with Applications 38 (2011) 10624–10630

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Estimating the shift size in the process mean with support vector regression and neural networks

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ARTICLE INFO

Keywords:
CUSUM
Mean shifts
Neural networks
Support vector regression

ABSTRACT

Control charts are usually used in manufacturing and service industries to determine whether a process is performing as intended or if there are some unnatural causes of variation. Once the control chart detects a process change, the next issue is to "search for assignable causes", or "take corrective actions", etc. Before corrective actions are taken, it is critical to search for the cause of the out-of-control situation. During this search process, knowledge of the current parameter level can be helpful to narrow the set of possible assignable causes. Sometimes, the process/product parameters might be adjusted following the out-of-control signal to improve quality. An accurate estimate of the parameter will naturally provide a more precise adjustment of the process. A distinct weakness of most existing control charts techniques is that they merely provide out-of-control signals without predicting the magnitudes of changes.

In this paper, we develop a support vector regression (SVR) model for predicting the process mean shifts. Firstly, a cumulative sum (CUSUM) chart is employed to detect shifts in the mean of a process. Next, an SVR-based model is used to estimate the magnitude of shifts as soon as CUSUM signals an out-of-control situation. The performance of the proposed SVR was evaluated by estimating mean absolute percent errors (MAPE) and normalized root mean squared errors (NRMSE) using simulation. To evaluate the prediction ability of SVR, we compared its performance with that of neural networks and statistical methods. Overall results of performance evaluations indicate that the proposed support vector regression model has better estimation capabilities than CUSUM and neural networks.

1. Introduction

Statistical process control (SPC) concepts and methods have been successfully implemented in manufacturing and service industries for decades. As one of the primary SPC tools, control chart plays a very important role in attaining process stability. Once the control chart detects a process change, the next issue is to "search for assignable causes", or "take corrective actions", etc. Before corrective actions are taken, it is critical to search for the cause of the out-of-control situation. During this search process, knowledge of the current parameter level can be helpful to narrow the set of possible assignable causes. Sometimes, the process/product parameters might be adjusted following the out-of-control signal to improve quality. An accurate estimate of the parameter will certainly provide a more precise adjustment of the process. A distinct disadvantage of most existing control charts techniques is that they purely provide out-of-control signals without predicting the magnitudes of changes, with the exception of the cumulative sum (CUSUM) control scheme (Page, 1961) and the exponentially weighted moving average chart (Roberts, 1959). When using the CUSUM schemes in monitoring the mean shifts, Montgomery (2005) provided an explicit form to estimate the magnitude of shifts. A modified EWMA procedure useful for estimating the new process mean can also be found in Montgomery (2005).

Estimating the process parameter is considered a difficult challenge in SPC. On the one hand we wish to detect the process changes as quickly as possible, and on the other we may have insufficient data points to estimate the new process parameter. Due to the advent of technological advancement and manufacturing automation, it is now feasible to apply more sophisticated monitoring procedures. In recent years, attempt to applying artificial neural networks (ANN) to process control have been studied by several researchers with significant results. Artificial neural networks can be used to analyze process status from input of control chart samples. For an in-depth review of the applications of neural networks for process monitoring, the reader is referred to Zorriassatine and Tannock (1998) and Barghash and Santarisi (2007). What follows is a brief review of previous applications of neural networks to statistical process control, as relevant to this study.

Chang and Aw (1996) developed a neural fuzzy control chart to detect mean shifts. Their network can also classify magnitudes of

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doi:10.1016/j.eswa.2011.02.121

the shifts in order to expedite the diagnosis of assignable causes. Guh and Hsieh (1999) proposed an artificial neural network based model, which contains several back propagation networks, to both recognize the abnormal control chart patterns and estimate the parameters of abnormal pattern. Guh and Tannock (1999) introduced a neural network-based approach to recognize control chart patterns and identify key parameters of the specific patterns involved. Their approach is applicable to both single and concurrent patterns.

Wang and Chen (2002) developed a neural-fuzzy model not only to identify mean shifts but also to classify their magnitudes. Chen and Wang (2004) also proposed a neural network approach for monitoring and classifying the mean shifts of multivariate process. Guh (2005) proposed a hybrid model integrating neural network and decision tree to detect and classify control chart patterns, and simultaneously estimate the major parameter of the detected pattern.

In recent years, the support vector machine (SVM) has been introduced as a new technique for solving a variety of learning, classification and prediction problems. There is also some research on using support vector machines to monitor process variation (Cheng & Cheng, 2008; Chinnam, 2002; Sun & Tsung, 2003). Support vector regression (SVR), a regression version of SVM, has been recently developed to estimate regression functions. Same as SVM, SVR is capable of solving non-linear problems using kernel functions and has been successful in various domains. In this paper, we propose using SVR to predict the magnitudes of process shift. Feed-forward neural networks with different training algorithms and CUSUM-based estimator are used as benchmarks for comparison.

Remaining of the paper is structured in the following manner. Section 2 explains the research methodologies adopted by this research, including the generation of training/test data, input vectors, and performance metrics. Section 3 presents a brief introduction to SVR and also describes the development of an SVR-based prediction model. Section 4 describes the prediction models constructed using neural networks. This section also describes the experiments performed to select the neural network model with the best performance. In Section 5, results of comparative study are discussed. The final section concludes the paper and provides suggestions for future research.

2. Research design

The proposed system is schematically illustrated in Fig. 1. It includes a shift detector and a prediction model. The traditional CUSUM chart works as a mean shift detector. Next, a prediction model is used to estimate the magnitude of shifts as soon as CUSUM signals an out-of-control situation. Note that this research formulated the shift characterization as a regression problem instead of a classification problem. This is a natural choice since the shift size $\Delta \in R$. Some researchers (see, for example, Chang & Aw, 1996; Chiu, Chen, & Lee, 2001; Chen & Wang, 2004) addressed the shift characterization as a multi-class classification problem. This approach would require too many output nodes, and is computation intensive. Trying to diminish the number of classes would lead to lower precision and lower performance.

The CUSUM control scheme is an effective alternative to the traditional Shewhart control chart. CUSUM procedure attempts to incorporate information from the entire set of data. Therefore, the CUSUM scheme can offer considerable performance improvement relative to Shewhart charts. The standardized CUSUM schemes for monitoring the process mean are based on the following recursive statistics,

$$C_i^+ = \max\{0.0, z_i - k + C_{i-1}^+\},$$
$$C_i^- = \max\{0.0, -z_i - k + C_{i-1}^-\}, \tag{1}$$

where z_i can be the standardized statistic of a single observed value or the average of several observed values taken at sampling time i. The parameter k is usually called the reference value or the slack value. The statistics C^+ and C^- are called one-sided upper and lower CUSUM charts, respectively. The starting values of CUSUM statistics are $C^+ = C^- = 0$. The CUSUM control chart signals if either C^+ or C^- exceed the decision interval h. In general, CUSUM control schemes require the setting of reference value k and decision interval h before implementation. A CUSUM with $k = 0.5$ and $h = 5.0$ has been widely used in practice. This CUSUM scheme was adopted in this research.

When using the CUSUM schemes in monitoring the mean shifts, Montgomery (2005) recommends the following equations to estimate the magnitude of shifts:

$$\hat{\Delta} = \begin{cases} k + \frac{C_i^+}{N^+} & \text{if } C_i^+ > h, \\ -k - \frac{C_i^-}{N^-} & \text{if } C_i^- > h, \end{cases} \tag{2}$$

where $\hat{\Delta}$ is the estimated magnitude of shift expressed in standard deviation units. The quantities N^+ and N^- are the number of consecutive periods that the CUSUM statistics C_i^+ and C_i^- have been nonzero. The CUSUM can be thought of as a weighted average of all past and current observations, in which we give equal weight to the last N^+ (or N^-) observations and weight zero to all other observations. Note that the weights are stochastic or random.

2.1. Selection of input vector

The proposed prediction model is based on the assumption that there are a number of observations ready for analysis. The number of data in a sequence provided to the prediction model is referred to here as the window size, m. There are many different elements that could be used to construct an appropriate input vector for this problem. Sample data are natural candidates for elements of input vector. In this study, the inputs used by a prediction model are the most recent m observations, whereas the output is the predicted size of the process shift. The prediction function has the form:

$$\Delta = f(V_{t^*}) = f(x_{t^*-m+1}, x_{t^*-m+2}, \ldots, x_{t^*}), \tag{3}$$

where t^* is the sample index when CUSUM signals an out-of-control situation, $V_{t^*} = \{x_{t^*-m+1}, x_{t^*-m+2}, \ldots, x_{t^*}\}$ and $\Delta \in \{-6, -5.75, \ldots, -1, +1, \ldots, +5.75, +6\}$.

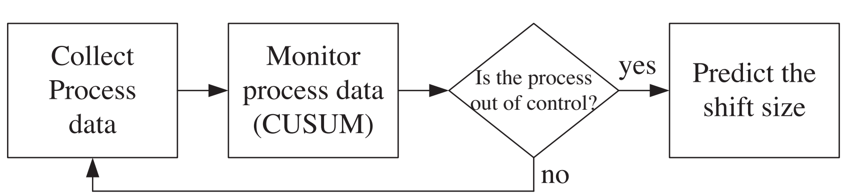

Fig. 1. General framework of the proposed system.