A Review for Manifold Learning-Based Statistical Process Control

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Abstract-**This paper reviews manifold learning-based multivariate statistical process control (MSPC) in manufacturing processes. Manifold learning is powerful technique in data analysis, pattern recognition, datamining, data visualization, etc. Those algorithms have been used widely in many industrial applications (e.g., image procesing, visual analysis, pattern recognition) and obtains many successes. This paper discusses the current states and new trends of manifold learning-based MSPC to provide a guidance for applications of manifold learning in mafacturing process quality control.**

Keywords - **Multivariate statistical process control, manifold learning, quality control**

I. INTRODUCTION

Jackson [1] stated that any process control in multivariate manufacturing processes should fulfill the following four conditions: (1) an answer to the question 'is the process in control' should be given; (2) the probability for the event 'false diagnosis for an abnormal process' must be specified; (3) the relationship among the process variables need to be considered; and (4) an answer to the question 'what does result in the out-of-control process' can be available. Over the last 30 years, statistical process control (SPC) has been widely applied in real-world, where the regular method is to maintain a separate chart (i.e., univariate control charts) like Shewhart, EWMA, CUSUM control charts for each considered process variable [2]. However, this could result in many false alarms when process variables are highly correlated. Dimension reduction has been employed to find a reduced data space where the significant pattern of the process data variation is faithfully represented. Thus, multivariate SPC (MSPC) based on some data projection methods like principal component analysis (PCA), partial least squares (PLS), etc. [3], has been applied to on-line manufacturing process monitoring [2, 4]. However, some unique characteristics (i.e., nonlinear or multimodal) in many manufacturing processes (e.g., semiconductor manufacturing) have posed some difficulties to regular PCA-based fault detection models. These typical characteristics make modeling of regular PCA-based T^2 and SPE to be difficult, which decreases performance of these monitoring methods, significantly.

As opposed to the globality-based data projection methods like PCA, locality-based methods, i.e., manifold learning, represented by Isomap [5], locally linear embedding (LLE) [6] and Laplacian eignmap (LE) [7] that seek to discover the nonlinear structure of the data manifold, appeared in the recent years. However, their nonlinear property results in high computational cost. Moreover, they yield mappings which are defined only on training dataset and thus it is very difficult to naturally evaluate these maps on testing dataset. Recently, a linear dimensionality reduction algorithm, called locality preserving projections (LPP) was proposed in [8]. LPP is a linear projective map that aims to solve a variational problem through optimally preserving the intrinsic geometry structure of the given data in a low-dimensional space. Various manifold learning algorithms have been applied in imaging processing, visual analysis, etc., and obtain many successes in these applications. Recently, manifold learning-based process monitoring methods have been proposed to overcome some limitations existing in PCA/PLS-based monitoring methods. In this paper, we mainly provide a review for manifold learning-based MSPC to provide a guidance for applications of manifold learning in manufacturing process quality control.

II. MANIFOLD LEARNING-BASED MSPC

This section firstly reviews the state-of-the-art of manifold learning-based MSPC. Secondly, the new tendency of manifold learning-based MSPC is further discussed to present the new applications of manifold learning in MSPC.

The local model that explicitly considers the manifold structure modeled by an adjacency graph is generally superior to a global model when it is applied in projection for complicated data with nonlinear distribution characteristic. Hu and Yuan [9] applied LPP-based MSPC to batch process monitoring. LPP is capable of finding more meaningful intrinsic information hidden in the process data, and thus shows better monitoring performance than PCA. LPP-based feature extraction and selection methods are also proposed for machine running quality assessment [10-11].

A batch process monitoring approach based on tensor locality preserving projections is proposed [12]. A dynamic multiway neighborhood preserving embedding (DMNPE)-based MSPC method is proposed for fed-batch process monitoring [13]. DMNPE aims to preserve local neighborhood structure of the given data to extract important local information for MSPC model. Different from conventional vectors-based monitoring models which consider the batch data as a vector, Tensor LPP (TLPP) that treats the batch data as a second order tensor, or matrix is also used for process monitoring. Shao et al. [14] proposed a nonlinear dimensionality reduction method called generalized orthogonal LLP (GOLPP) for fault detection and diagnosis in manufacturing processes. GOLPP is an extensive algorithm of linear orthogonal LLP (OLPP) for nonlinear processes using the kernel-trick. The experimental results on simulation processes show the superiority of the GOLPP-based fault detection and diagnosis methods over popular nonlinear methods.

In many situations, manifold learning can recover important aspects of the intrinsic linear or nonlinear manifold structure by preserving local structure of the given data. However, they generally focus on local information preservation in the given data and thus could loss nonlocal information [15]. Yu [16] proposed local and nonlocal preserving projection (LNPP) algorithm for complicated multivariate process control. Because of its ability to discriminate directions with the local and nonlocal structure information in the given data, LNPP shows high performance for extracting effective features from process signals (e.g., high dimensional process variable set from semiconductor manufacturing processes). LNPP-based MSPC has been applied successfully to machine health degradation assessment [17].

Some extensive algorithms of LPP and PCA which aim to preserve local and global information from the given data are also investigated in recent years. Zhang et al. [18] proposed a global-local structure analysis (GLSA) model through combining PCA and LPP, and their process monitoring method outperforms PCA and LPP-based monitoring methods. Motivated by the manifold learning method-based process control methods proposed by Zhang et al. [18-19], Yu [20] proposed a local and global PCA (LGPCA) for process monitoring and fault diagnosis in MSPC, which shows better performance than PCA.

From the viewpoint of data analysis, data projection, pattern recognition and information retrieval, these representative manifold learning algorithms (e.g., LPP, GLSA, LNPP) have distinct advantages in the following aspects:

(1) The representative manifold learning algorithms share many of the properties of nonlinear techniques such as LLE [6] and LE [7]. Thus, they are capable of revealing the intrinsic geometrical structure of the given data and obtaining more useful low-dimension information hidden in the high-dimensional data than PCA.

(2) They are linear. This makes them fast and suitable for real-world applications.

(3) The robustness of these representative manifold learning algorithms is relatively good due to local information preservation, so it is less sensitive to outliers than PCA.

Based on the excellent performance of manifold learning for dimension reduction and information extraction, the following studying of manifold learning and its applications in MSPC could be performed in future: (1) More effective manifold learning algorithms that aim to extract more effective information hidden in high data space will be proposed; (2) Various extensive methods to manifold learning-based MSPC, like dynamic, multiway, adaptive manifold learning, etc., will be developed to solve various problems existing in complicated manufacturing processes; (3) Manifold learning-based fault diagnosis in processes will be investigated; (4) The combination of manifold learning and other machine learning algorithms will be further explored for process monitoring, fault diagnosis, fault isolation, etc.

V. CONCLUSION

In this paper, firstly, the characteristics of the representative manifold learning algorithms are discussed through comparison with PCA. Secondly the status of manifold learning-based MSPC in recent years is reviewed. Finally, the new trends in manifold learning-based MSPC are discussed. The intension of this review is to provide an alternative MSPC approach for the process control research community so that utility of manifold learning algorithms can be examined in some complicated cases in which the regular MSPC does not work well.

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