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Inter-batch-evolution-traced process monitoring based on inter-batch mode division for multiphase batch processes

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ABSTRACT

The multiplicity of operation phases is an inherent nature of many batch processes and each phase exhibits significantly different behaviors. Besides process variation along the time direction within each batch, process variation along the batch direction, called inter-batch evolution here, widely exists in batch processes. Inter-batch evolution has caused different operation modes along the batch direction, which may not be well captured by a single model. In this work, the inter-batch evolution is tracked, based on which multiple modes are separated and modeled for online process monitoring along the batch direction. First, a batch cycle is divided into multiple phases. Then sliding windows are constructed for analysis of the inter-batch evolution within each phase. Based on the comparison between reference windows and sliding windows, different process modes are separated in order along the batch direction. Four monitoring subspaces which cover different types of relative variations are used in monitoring. During online monitoring, these different variations are then supervised respectively to trace the inter-batch evolution. The application to a typical multiphase batch process with inter-batch evolution, injection molding start-up process, illustrates the feasibility and performance of the proposed algorithm.

1. Introduction

As one important type of production, batch processes are widely applied in different industrial fields. To meet the requirements of fast changing markets and to manufacture higher-value-added products in batch processes, operation safety has drawn people's attentions [1–4]. Batch processes usually have complicated characteristics which make it difficult to build a first-principle model within a limited time period. On the other hand, with the development of computers and sensors, abundant process data are available covering much process information. Therefore, multivariate statistical process control (MSPC) methods, using techniques such as principal component analysis (PCA) [5,6] and partial least squares (PLS) [7,8], which can extract process characteristics purely based on process data, have been successfully developed. Then, multiway principal component analysis (MPCA) [9] and multiway partial least square (MPLS) [10] were proposed to handle the three-dimensional data structure of batch processes, $\underline{\mathbf{X}}(I \times J \times K)$, comprised of the variable direction (j), the time direction within a batch cycle (k) and the batch direction throughout the whole operation (i), shown in Fig. 1(a). However, it is difficult for MPCA and MPLS to reveal the changes of process correlations along the time direction since the entire batch process data was taken as a single object. Also, it is difficult for online application because the whole new batch data is not available up to the concerned time so that the unknown future values have to be estimated.

Multiphase is another significant feature of batch processes. In general, multiple operation steps are included in each batch cycle, resulting in different process segments, called stages or phases [11–14], which represent the process variation in the time direction within a batch cycle as shown in Fig. 1(b). In this work, phases are preferred. A series of phases comprises a batch cycle and each phase has its own characteristic, which requires special attention for multiphase batch process monitoring. Some works [11–21] have been done focusing on multiphase characteristic of batch processes since the 1990s. Different statistical models were established to capture different characteristics of different phases on the basis of such recognition that the underlying variable correlations are similar within the same phase and different across phases. Following multi-phase feature, transitions between neighboring phases [16–18] and uneven-duration problem [19–21] were investigated based on phase characteristics for both process monitoring and quality analysis.

Besides, process variation exists in batch processes due to various factors, such as catalysis deactivation, sensor drifting, equipment aging and environment change [22]. As shown in Fig. 1(c), the process variation in the batch direction throughout the whole operation leads to

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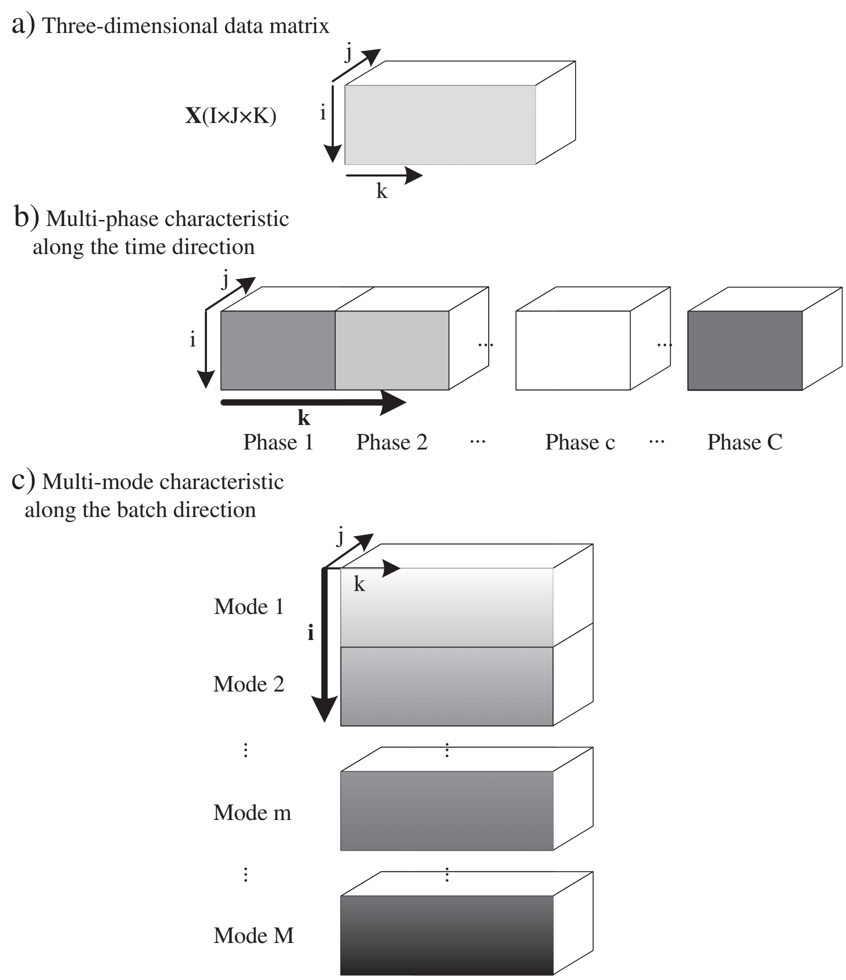

Fig. 1. Data characteristics of batch processes.

different process modes with different process characteristics. Some techniques have been proposed to handle process variations by model adaptation, such as consecutively updated MPCA [23,24]. The basic idea of these methods is to consecutively and directly adjust the statistical monitoring model by embracing new normal measurements. However, these methods barely evaluate the changes of monitoring models along the batch direction, in which, models are in general updated arbitrarily, increasing the chance of introducing disturbances into the process model. Also, there are multimode methods proposed to build different models for different modes [25,26]. But the process variation along the batch direction may be too slow and continuous to be divided into several modes using these multimode methods proposed for processes with multiple steady states. It is interesting to analyze the change rules of process variation along the batch direction to divide the entire batch process with a series of batches into different modes and thus build different monitoring models for these modes. The process characteristic variation along the batch direction caused by process dynamics or long term external factors is called inter-batch evolution here against the random variation caused by noises. Inter-batch evolution analysis may provide more information for batch process understanding and monitoring.

Therefore, in the present work, the inter-batch evolution along successive batches is addressed for statistical modeling and online monitoring of multiphase batch processes. PCA is used as the basic statistical analysis tool to monitor successive batches. Different process modes are separated along the batch direction by the inter-batch evolution analysis, and monitoring models will be built for those process modes obtained. Besides, considering that multiphase characteristic is a major nature of many batch processes, inter-batch evolution characteristics will be analyzed in each specific phase and different monitoring models will be built for different phases. To analyze the inter-batch evolution, reference windows and sliding windows are constructed including several batches to judge new modes when sliding windows present significant difference from the reference window. Multiple modes are thus separated along the batch direction. Also, four subspaces are decomposed and modeled for online monitoring separately, revealing changes of different process variations.

The rest of this paper includes four parts: first, the PCA based fault detection algorithm is briefly revisited in Section 2. Then the proposed method is presented in Section 3, including the phase-based inter-batch evolution analysis, statistical modeling and online process monitoring. In Section 4, the application of the proposed method to a real industry, the injection molding start-up process which has the typical multiphase and inter-batch evolution nature, is presented and discussions are conducted based on the illustration results. At the last, the conclusion is drawn.

2. Principal component analysis based fault detection

In this subsection, the PCA based fault detection system is described. In general, it uses two subspaces, principal component subspace and residual subspace (PCS and RS) to monitor different types of process variations. Two different monitoring statistics are used, Hoteling-T^2 and *SPE*, reflecting the abnormal changes in each subspace.

Let $\mathbf{X}$ be an $N \times J$-dimensional normal data matrix in which the rows are the observations and the columns are process variables. It is