Difference-Based Dynamic Weighting SVDD for Multimodal Process Fault Detection: A Postprint

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Date: 2018-10-11T00:00:00+00:00

Abstract

Modern industrial production processes feature multiple operating modes with strong correlations among data sequences. As a single-mode static fault detection algorithm, traditional SVDD cannot guarantee both accuracy and real-time performance for fault detection in multi-mode dynamic processes. To address this problem, a Nearest Neighbor Difference Weighted Dynamic SVDD detection method (NND-DWSVDD) is proposed. Firstly, NND is employed to eliminate the multi-mode structure of the data, ensuring that the process data conforms to a unimodal distribution; secondly, dynamic methods are introduced to the differenced data and weights are assigned to highlight useful information; finally, the SVDD method is utilized to construct a monitoring model for online monitoring. NND-DWSVDD enhances the fault detection rate for multi-mode dynamic processes. For fault detection in multi-mode dynamic processes, NND-DWSVDD does not require multi-model modeling but only a single model, satisfying the requirements of single-mode fault detection. The effectiveness of the proposed method is verified through multi-mode numerical examples and semiconductor manufacturing process data.

Full Text

Application of Dynamic Weighted SVDD Based on Difference in Multi-Modal Process Fault Detection

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Abstract

Modern industrial production processes exhibit multiple operating modes with strong correlations between data sequences. Traditional Support Vector Data Description (SVDD), as a single-mode static fault detection algorithm, struggles to ensure both accuracy and real-time performance for multi-modal dynamic process fault detection. To address this limitation, this paper proposes a Nearest Neighbor Difference-based Dynamic Weighted SVDD (NND-DWSVDD) method. First, the Nearest Neighbor Difference (NND) technique eliminates multi-modal structures in the data, ensuring the process data follows a unimodal distribution. Next, a dynamic approach is introduced for the differenced data, with weights applied to highlight useful information. Finally, an SVDD-based monitoring model is established for online monitoring. NND-DWSVDD improves fault detection rates for multi-modal dynamic processes. For multi-modal dynamic process fault detection, NND-DWSVDD does not require multi-model modeling but only a single model, satisfying single-mode fault detection requirements. The effectiveness of the proposed method is validated through multi-modal numerical examples and semiconductor production process data.

Keywords: multi-modality; nearest neighbor difference; dynamic weighting; support vector data description; fault detection

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1. Introduction

As modern industrial structures become increasingly complex, demands for production process safety and reliability continue to grow [1,2]. Timely and effective monitoring of operating systems represents an effective method for improving work efficiency and ensuring production safety [3,4].

In the late 1990s, Tax et al. [5] proposed the Support Vector Data Description (SVDD) method, which maps low-dimensional spatial data to a high-dimensional feature space through nonlinear transformation. This approach does not require data to follow a Gaussian distribution and can be applied to data with nonlinear relationships between variables. Scholars have conducted extensive research on this method [6–10]. However, the above methods assume during modeling that observation data at a given moment is independent of past data. While this assumption is valid when sampling intervals are long, actual industrial production requires shorter sampling intervals for better process monitoring. Therefore, exploring monitoring methods suitable for sequentially correlated data is essential. Sun et al. [11] proposed a sliding window SVDD-based fault detection method that gradually updates the current sub-data space using appropriately sized sliding windows, improving detection performance compromised by dynamic characteristics in data. However, this method requires continuous updating of sub-models, significantly reducing operational efficiency. To address problems where fault models are unknown and fault sample data are difficult to obtain, Duan et al. [12] proposed an SVDD-based internal sensor fault detection method for mobile robots. Assuming only normal model samples are available, the method first establishes a compact hypersphere based on SVDD for these normal samples, then validates new test data using the resulting hypersphere.

For a new sample, its distance to the hypersphere center can be expressed as:

$$D = 1 - 2\sum_{i} \alpha_i K(x_{new}, x_i) + \sum_{i,j} \alpha_i \alpha_j K(x_i, x_j)$$

In recent years, multi-modal fault detection has attracted widespread attention from scholars. In multi-modal problems, each mode exhibits significantly different data centers and covariances, with data centers and distributions varying substantially across modes. Traditional SVDD algorithms, as single-classification methods, cannot detect multi-modal faults. To solve this problem, multi-modal fault detection methods based on SVDD have gradually emerged. Wang et al. [13] proposed a fuzzy clustering multi-model inference detection method to search for optimal clustering centers in process data. Zhao et al. [14] proposed a new algorithm based on a Weighted Local Standardization (WLS) strategy for SVDD, which standardizes multi-modal data to eliminate multi-modal characteristics and normalize them into unimodal data distributions. Li et al. [15] proposed a Local Density Ratio-weighted SVDD (LDR-wSVDD) method for multi-modal process fault detection to address multi-modal process monitoring problems with varying densities and outliers in training samples.

This paper comprehensively considers sequential correlations in sampling data and existing multi-modal, multi-operating-condition problems, proposing a real-time online multi-modal fault detection method based on Nearest Neighbor Difference-weighted Dynamic SVDD (NND-DWSVDD). This method not only solves the problem of poor detection performance caused by traditional SVDD ignoring sequential correlations in data but also enables SVDD to detect multi-modal faults, significantly improving algorithm detection efficiency and capability.

2. Dynamic Weighted SVDD Based on Difference Method

For traditional SVDD algorithms, when multi-modal structures exist in training data, the single-mode modeling condition cannot be satisfied, and SVDD detection performance will inevitably be compromised. Particularly when faults occur between multiple modes, SVDD detection performance becomes even less ideal. To improve SVDD detection capability for multi-modal dynamic data, this section introduces difference data preprocessing techniques and dynamic weighting methods.

2.1 Nearest Neighbors Difference (NND)

Zhang et al. [16] proposed the nearest neighbor difference method. The basic principle is as follows: Assume the original dataset X contains n samples with m variables (where n represents sample size and m represents the number of measured variables). The first neighbor of x_i is x_i^*, determined by comparing the Euclidean distance from sample x_i to other samples.

First, sample x_i finds its nearest neighbor x_i^* in the training set, then performs first-order difference operation using equation (6):

$$\hat{x}_i = x_i - x_i^*$$

To solve the problem of uneven data distribution caused by different variances, this paper calculates second-order differences while introducing weight parameters, converting equation (6) to equation (7):

$$\hat{x}_i = w_i(x_i - x_i^*)$$

where $w_i = 1/\|x_i - x_i^*\|$ is the difference matrix. Under normal conditions, since sample x_i and its nearest neighbor x_i^* are close in space, the difference values will be distributed around the origin.

2.2 Dynamic Weighting

In dynamic systems, current moment data depends on past moment values, requiring understanding of the relationship between current and past moments. From Section 2.1, we obtain the differenced unimodal data $\hat{X}$. Adding previous h moment observation data yields the augmented matrix:

$$X_a = [x_t^T, x_{t-1}^T, \dots, x_{t-h}^T]^T$$

where x_t is the collection of m-dimensional observation variables at time t; h is the time lag length, typically calculated using parallel analysis. To reduce complexity and runtime, the augmented matrix is processed as follows:

$$\tilde{X}_a = \frac{1}{h+1} \sum_{i=0}^{h} x_{t-i}$$

To highlight useful information in variables, this paper defines a weight matrix W with the specific calculation formula:

$$W_r = \frac{\mathrm{std}(X_h)_r}{\sum_{m=1}^{M} \mathrm{std}(X_h)_m}, \quad r = 1, 2, \dots, m$$

where $\text{std}(X_h)_r$ is the standard deviation of the r-th variable in training data; the weight matrix W is a diagonal matrix. In collected data, if a variable contains more information, it is assigned a larger weight; otherwise, it receives a smaller weight. Through weighting, important information is prominently displayed.

The weighted matrix becomes:

$$W = \text{diag}(W_1, W_2, \dots, W_m)$$

$$\tilde{X}_h = X_h \times W$$

3. Fault Detection Based on NND-DWSVDD

To solve multi-modal problems in industrial production processes, this paper proposes an NND-DWSVDD-based fault detection method. First, multi-modal data is preprocessed using the NND method to ensure data follows a unimodal distribution. Second, a dynamic approach is introduced for the differenced unimodal data to address cross-correlation and autocorrelation in the data. Then, weighting factors are applied to dynamic data to highlight important information. Finally, an SVDD detection model is established to detect faults in new data. The modeling and fault detection steps of the NND-DWSVDD algorithm are shown in Figure 1 [Figure 1: see original paper].

4. Simulation and Analysis

To verify theoretical feasibility, this chapter conducts comparative experiments using both traditional SVDD and the proposed NND-DWSVDD methods on multi-modal numerical examples and semiconductor process data, with results and analysis presented concurrently.

4.1 Numerical Example

Ge et al. [17] proposed a typical multi-modal model widely used by scholars to validate algorithms for complex data. This paper adopts this model to verify NND-DWSVDD effectiveness, with the model structure shown in equation (12):

$$\begin{cases} x_1 = s_1 + 0.5768e_1 + 0.3766e_2 \\ x_2 = s_1 + 0.7382e_1 + 0.0566e_2 \\ x_3 = s_2 + 0.8291e_1 + 0.4009e_2 \\ x_4 = s_1 + 0.6519e_1 + 0.2070e_2 \\ x_5 = s_2 + 0.3972e_1 + 0.8045e_2 \end{cases}$$

The model includes five variables x_1, x_2, x_3, x_4, x_5. s_1 and s_2 are latent variables; e_1, e_2, e_3, e_4, e_5 are five independent noise terms following a Gaussian distribution with mean 0 and standard deviation 0.01. Two designed modes are:

- Mode 1: $s_1 \sim \mathcal{U}(10, 7)$, $s_2 \sim \mathcal{N}(15, 1)$
- Mode 2: $s_1 \sim \mathcal{U}(2, 5)$, $s_2 \sim \mathcal{N}(7, 1)$

400 samples are generated under each mode to form the normal training dataset. Two test datasets are generated using equation (12). The following faults are introduced:

a) System operating in Mode 1: Add a step signal with amplitude 4 to x_1 starting at moment $T = 401$
b) System operating in Mode 1: Add a ramp signal with amplitude 0.02 to x_2 starting at moment $T = 401$

To more clearly observe the ability of difference processing for multi-modal data, this paper presents histograms of variables x_1, x_2 before and after difference processing for both normal and fault data. Figure 2 [Figure 2: see original paper] shows data distribution after Z-SCORE standardization in SVDD, while Figure 3 [Figure 3: see original paper] shows data distribution after NND difference processing in NND-DWSVDD. The comparison clearly demonstrates NND' s capability in processing multi-modal data.

Having obtained single-mode data through the previous difference processing step that addressed cross-correlation issues, we next examine the dynamic characteristics (autocorrelation) of the data. The weighting method highlights important information and resolves linear relationships between different variables. For visualization, Figures 4 [Figure 4: see original paper] and 5 [Figure 5: see original paper] are provided.

Figures 6 [Figure 6: see original paper] and 7 [Figure 7: see original paper] show detection results for both methods on the two fault types. The detection plots reveal that when step faults occur between two modes, SVDD can hardly detect the fault. This is because SVDD neither considers data autocorrelation nor cross-correlation (multi-modality). Using Z-SCORE for data processing is effective when data follows the same distribution, but when faults occur across multiple modes, Z-SCORE cannot eliminate multi-modal structures due to its algorithmic limitations. Consequently, SVDD establishes an overly large model during the modeling phase, causing faults to be enclosed within the hypersphere as normal data. NND-DWSVDD eliminates multi-modal structures during data processing and introduces weighting factors to highlight important information, ensuring SVDD can establish an appropriate single-mode model. When ramp faults occur, both methods exhibit detection delays, but NND-DWSVDD shows significantly reduced delay time compared to SVDD, laying the foundation for timely fault detection and reducing production losses.

4.2 Semiconductor Process

The semiconductor data applied in this paper [18] originates from actual semiconductor production process data from Texas Instruments. The dataset consists of 3 modes with 108 normal wafers and 21 faulty wafers. Due to missing data in 2 batches (the 56th normal batch and 12th fault batch), the actual dataset contains 107 normal batches and 20 fault batches. Among the 107 normal batches, batches 1–34 represent Mode 1, 35–66 represent Mode 2, and 71–107 represent Mode 3. The original dataset contains 40 variables. In this experiment, 17 variables are selected from the 40 measurement variables as detection variables, with 96 normal batches randomly selected as modeling data, 6 normal batches as validation data, and 20 fault batches for testing. Each batch has unequal length, with duration varying between 95–112 s.

Traditional statistical analysis methods typically use the shortest length method to address unequal-length batch process problems. While simple, this approach loses substantial process information from data trajectories and reduces point-to-point data correlation, compromising data reliability. To improve fault diagnosis performance for unequal-length batch processes, this paper employs statistical pattern analysis algorithms [19] to preprocess multi-modal data. All statistical features are combined into an m-dimensional feature vector, followed by difference operations on statistical patterns. Finally, corresponding statistical measures are calculated for the resulting statistical difference data matrix and compared with control limits to determine detection results.

For a batch I with n samples and m variables, the mean and variance of each variable are calculated separately, then define vector $SPC = [\mu, \sigma]$, where μ is the mean vector and σ is the variance vector.

Figure 8 [Figure 8: see original paper] shows SVDD detection results for 21 fault batches. Traditional SVDD standardizes data using Z-SCORE without considering multi-modal effects or data autocorrelation, leading to inaccurate fault detection. Figure 9 [Figure 9: see original paper] shows NND-DWSVDD detection results for fault data. NND-DWSVDD considers data distribution characteristics, eliminating multi-modality during preprocessing to lay the foundation for subsequent detection. The dynamic weighting method then uses weighting factors to highlight important information while removing data autocorrelation, further ensuring detection effectiveness. Table 1 compares detection results for the 20 fault batches between both algorithms.

5. Conclusion

To address SVDD' s poor performance in detecting multi-modal faults in industrial production, this paper proposes a multi-modal industrial process fault detection method based on NND-DWSVDD by analyzing spatial distribution and correlation of data. The method first uses nearest neighbor difference to preprocess data, eliminating multi-modal forms caused by different centers. Second, a dynamic approach is introduced for the differenced unimodal data to remove data autocorrelation and ensure mutual independence. Finally, SVDD is applied for online monitoring. Compared with SVDD, NND-DWSVDD not only solves SVDD' s inability to handle multi-modal problems but also considers data autocorrelation, significantly improving fault detection rates.

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Note: Figure translations are in progress. See original paper for figures.