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Distribution Adaptation and Manifold Alignment for complex processes fault diagnosis

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ABSTRACT

The challenge faced by complex process fault detection is how to adapt the knowledge acquired on a source domain to a new different but related target domain. And the situation of none labeled data in target domain is considered to be more practical and challenging. In this paper, we propose a novel unsupervised domain adaptation approach that reduces distribution shifts for cross-domain fault detection, referred to as Distribution Adaptation and Manifold Alignment (DAMA). In DAMA model, we learn two projection matrices that map the monitoring data of source domain (labeled data) and target domain (unlabeled data) into two low-dimensional subspaces where the distributional shift and structural shift are reduced simultaneously and then establish a monitoring model on the old process by LSSVM to monitor the new process data. The main contributions of the presented approach are as follows: 1) We introduce manifold alignment into unsupervised domain adaptation, which can preserve the neighborhood relationship within each set and make the distance of the corresponding points in the projection coordinates as close as possible. 2) It is also suitable for the complex process with nonlinear trait. 3) To our knowledge, it is a pioneering work to apply domain adaptation methods to the field of fault diagnosis. This method can obtain the results of fault detection and fault diagnosis in the monitoring process simultaneously. The experiments on TE process and real ore grinding-classification process verify the effectiveness and practicability of the proposed method.

1. Introduction

With the continuous development of modern industry and the continuous improvement of the automation level, industrial production is moving towards the direction of large-scale, high-speed, continuous and automatic production. Industrial production processes such as iron and steel metallurgy, petroleum refining, chemical, power, thermal and other industries, the poor production environment of which is usually in the high temperature, high pressure or low temperature vacuum. The production process also contains complex physical and chemical processes and the existence of various mutations and uncertainties makes industrial processes usually complex. If we neglect detection or operate improperly, a tiny fault can be propagated and amplified, resulting in the failure of production and even the paralysis of the overall system. The occurrence of faults in industrial processes will not only affect product quality, increase equipment maintenance costs and increase production costs, in severe cases, even cause catastrophic events such as fires and explosions which will bring serious economic losses to social production and a serious threat to people's life security.

With the increasing complexity of industrial processes, it is becoming increasingly important to detect faults in industrial processes [1]. Fault detection and separation are important and challenging problems in many engineering applications and continue to be an active area of research in the control community [2]. The purpose of fault detection and diagnosis is to identify the abnormal state and ensure that the industrial process runs smoothly according to the plan. Effective fault diagnosis can continuously analyze the process quantitatively or qualitatively, and alarm in time when finding abnormal. It helps on-site staff adjust operation and eliminate anomalies, so as to prevent catastrophic accidents.

With a large number of new instruments, networked instrumentation and sensing technology used in the whole process of manufacturing, a large number of process data is collected and stored, making the data-driven fault detection and diagnosis method become the mainstream technology of today's process monitoring. It uses the collected data to diagnose the state of the system running and fault information, without the need for complex mathematical models and accurate prior knowledge, greatly improving the efficiency and accuracy of industrial process fault diagnosis, reducing the risk of industrial production, and promoting the modern industrial development.

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In many machine learning algorithms, such as support vector machine [3] and neural network [4], a major assumption is that the training and the test data are drawn from the same distribution. Unfortunately, this assumption does not hold for many real applications. For example, in the complex industrial production process, the distribution of training data and test data will be discrepant due to the variation of the raw material and equipment structural parameters. In this case, the old process data can not be directly applied to the new production process. If we want to achieve fault diagnosis of different but similar production processes, we need to introduce new machine learning methods to establish a monitoring model. From this point of view, we can use the information of related industrial fields, in limited conditions as much as possible to improve the accuracy of fault diagnosis and reduce divergence of domain, that is, introducing the idea of domain adaptation into machine learning. Domain adaptation reduces the distribution divergence before establishing appropriate monitoring model. Domain adaptation has proven to be promising in image classification [5,6], object recognition [7,8,9,10], feature learning [11,12,13], sentiment analysis [14,15], document categorization across different customer datasets [16,17,18] and 3D pose estimation [19]. However, the application of recognizing fault information in the industrial field is very few. This paper combines domain adaptation with complex industrial processes to solve the problem of cross-domain fault categories separation with two different but similar data distribution.

As we known, labeling data is labor intensive and expensive, so it is impractical to mark large amounts of data in the new domain. Thus, domain adaptation can be used to employ previously labeled source domain data to boost tasks in a new target domain. Based on the availability of target labeled data, domain adaptation can be generally divided into semi-supervised and unsupervised domain adaptation. In this paper, we focus on unsupervised domain adaptation which is considered to be more practical and challenging.

In this paper, we propose a unified framework to simultaneously reduce the distributional divergence of data, geometrical shift and structural shift simultaneously. Specifically, we learned two coupled projections to map source data and target data into respective subspaces. After the projections, 1) the variance of target domain data is maximized to make the target domain better distinguishable, 2) the linear discriminative information of source data is preserved to effectively transfer the class information, 3) both the marginal and conditional distribution divergences between source and target domains are minimized to reduce the domain shift statistically, 4) the divergence of two projections is constrained to be small to reduce domain shift geometrically, and 5) in the embedded space, the local geometry of each manifold does not change and the distance between the corresponding points of the different data sets is as close as possible after alignment. In addition, our method can also deal with the situations where the shift between domains are nonlinear in a Reproducing Kernel Hilbert Space using some kernel functions Φ. The objective function can be solved efficiently in a closed form. The main contributions of this paper are as follows: (1) Unlike the existing process monitoring methods that the fault detection and fault diagnosis were completed in a different time, our method can obtain the results of the fault detection and fault diagnosis in a monitoring process simultaneously. In addition, we can also solve the problem of complex process data with nonlinear trait. (2) Different from most machine learning algorithm, our method breaks the assumption that the source domain and the target domain have independent and same distribution (both marginal and conditional distribution). We learn two projection matrices that map the monitoring data of source domain (labeled data) and target domain (unlabeled data) into two low-dimensional subspaces where the distributional shift and structural shift are reduced simultaneously. (3) We introduce manifold alignment into unsupervised domain adaptation. We dig deep into the intrinsic structure of the data itself by using the graph Laplacian matrix to approach the local manifold of the data in order to make the distance of the corresponding points in the projection coordinates as close as possible. (4) It is also suitable for the complex process with nonlinear trait. (5) To our knowledge, it is a pioneering work to apply domain adaptation methods to the field of fault diagnosis.

In this paper, we present an unsupervised domain adaptation method of fault detection and fault diagnosis based on process data. The rest of this paper is organized as follows. Section 2 is devoted to the presentation of the related work. In Section 3, we introduce fault diagnosis based on our method. Section 4 is dedicated to the experimental comparison performed on TE process and real ore grinding-classification process and the conclusions are drawn in Section. 5.

2. Related work

The main methods of fault diagnosis are analytic model-based method, knowledge-based method and data-driven method. The analytic model-based fault diagnosis method needs to establish an accurate mathematical model, which is often used in the case of less monitoring process parameters. The knowledge-based fault diagnosis method needs to combine prior knowledge with process data diagnosis. This method is also suitable for situations with fewer process parameters. With the increase of parameter, the diagnosis is more and more difficult. At present, the most popular method is a fault diagnosis method based on data-driven. The advantage of it is that it does not need to establish an accurate mathematical model and the required prior knowledge is less, only rely on the analysis of process data can diagnose faults. The weakness is that its effect relies on the quality and quantity of data.

The fault diagnosis methods based on data-driven are mainly statistical analysis methods, signal analysis methods and machine learning methods. Multivariate statistical methods include principal component analysis (PCA) [20], independent component analysis (ICA), partial least squares (PLS) [21] and Fisher discriminant analysis (FDA). The abrupt signals in process fault signals are generally divided into two categories: edge jump and peak jump. Methods based on signal processing is the use of signal processing techniques of signal decomposition, get the relevant characteristics of the time domain and frequency domain. Signal processing methods generally include spectral analysis, wavelet transform, S transform and HHT. The main methods of machine learning are artificial neural networks [22], SVM [23], and fuzzy logic, etc. Artificial neural network method needs to establish fault recognition and classification mapping, and mapping can be trained into a fault diagnosis network system. The fault condition is obtained by comparing the industrial operation observation data with the fault diagnosis. The method based on support vector machine is a kind of classification technology. When the training data is small samples can exhibit very good classification effect. Its core idea is: when the original data can not be separated, the low dimensional data through kernel function mapping data to the higher dimension space, so you can choose more parameters to increase the accuracy of fault identification. The method of fuzzy logic is mainly to fuzz the amount of data collected by the process data, and then the model is judged by the analysis.

However, the existing fault diagnosis methods are based on the assumption of independent and identically distributed. Therefore, when the distribution of monitoring data and training data is different, we urgently need a new method of fault diagnosis to solve this problem. The transfer learning method arises at the historic moment. A large number of methods have emerged [24,25].

According to the different contents to transfer, domain adaptation can be divided into instance-based adaptation, feature representation adaptation, and classifier-based adaptation [26,27].

Instance-based adaptation is that the error minimization reference model of the target domain is trained by applying the sample weight to the source domain, realizing the conversion of the source domain probability distribution to the target domain probability distribution. The core question is how to calculate the “weight”. The current methods are: the importance sampling method, the nuclear mean matching method and TrAdaBoost method.