Fault Diagnosis Using the Incremental Learning Algorithm with Support Vector Machine

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Abstract

To prevent process interruption and eventual losses, the need for a reliable fault detection and diagnosis system (FDD) is completely acknowledged. Besides the capability to recognize known faults automatically, a further requirement for a FDD is adaptability. If the model cannot be adapted to deal with changes, variations due to external changes, decaying performance, Poisoning of catalyst etc. the FDD system could perform misleadingly.This paper presents an advantageous of incremental learning algorithm for fault diagnosis, when a support vector machine algorithm are implemented as a classifier. The method which is followed in order to use the incremental learning algorithm is based on hyperplane-distance (HD)[1] . In the continues reactor which is studied, two cases are compared in order to clarify the role and importance of incremental learning algorithm. Result show the effectiveness of this method

Introduction

Fault detection and diagnosis (FDD) is an important first step in abnormal events management (AEM). Fault diagnosis in industrial processes are challenging tasks that demand effective and timely decision making procedures under the extreme conditions of noisy measurements, highly interrelated data, large number of inputs and complex interaction between the symptoms and faults. When it comes to data-driven models it could be seen that there is an increasing interest in the development of fault detection and diagnosis systems based on them. Venkatasubramanien [2], reviews and discusses fault diagnosis methods that are based on historic process knowledge. Qin [3], reviewed many basic and advanced issues in data-driven process monitoring, including fault detection, identification, reconstruction, and diagnosis.

With the increase in the size of the real-world data set, there are ever-increasing requirements to scale up the inductive learning algorithms. Incremental learning techniques are one of the possible solutions to the scalability problem. Various methods have been presented in the literatures about incremental learning, such as Schlimmer and Granger[4] , Schlimmer and Fishe [5]. Incremental learning for SVM was first introduced by Syed et al.[6] , who presented incremental strategies and proved that the support vector set, is a minimum set of the data set through experiments..

Among different methods for machine learning, support vector machine(SVM) is a method developed by Vapnik and co-workers [7]. There have been many researches about the theory and applications of SVM, and it has become one of the most useful methods of solving the problems in machine learning with good generalization performance. The key to construct optimal hyperplane, in SVM, is to collect more useful data as support vectors during the incremental learning. Most incremental learning algorithms improve SVM training process through collecting more useful data as support vectors [8][9]. As opposed to other learning methods such as neural networks, they are strongly theoretically founded, and have been shown to enjoy excellent performance in several applications.

Li, research on geometric character of support vector machine and proposes hyperplane distance-support vector machine (HD-SVM)[1]. According to the geometric character of support vector, the algorithm uses Hyperplane-Distance to extract the samples, selects samples which are most likely to become support vector to form the vector set of edge, and conducts the support vector machine training on the vector set. Using this method reduces the number of training samples and effectively improves training speed of incremental learning.

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