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Online fault diagnosis method based on Incremental Support Vector Data Description and Extreme Learning Machine with incremental output structure

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ABSTRACT

Online fault diagnosis system should be able to detect faults, recognize fault types and update the discriminating ability and knowledge of itself automatically in real time. But the class number in fault diagnosis is not constant and it is in a dynamic state with new members enrolled. The traditional recognition algorithms are not able to update diagnosis system efficiently when the class number of failure modes is increasing. To solve the problem, an online fault diagnosis method based on Incremental Support Vector Data Description (ISVDD) and Extreme Learning Machine with incremental output structure (IOELM) is proposed. ISVDD is used to find a new failure mode quickly in the continuous condition monitoring of the equipments. The fixed structure of Extreme Learning Machine is changed into an elastic structure whose output nodes could be added incrementally to recognize the new fault mode efficiently. Recognition experiments on the diesel engine under eleven different conditions show that the online fault diagnosis method based on ISVDD and IOELM works well, and the method is also feasible in fault diagnosis of other mechanical equipments.

1. Introduction

During fault diagnosis research of equipments, it is impossible to get all the failure data of the equipments in advance, so fault classification based on pattern recognition is a method of making decision under incomplete information. Acquisition of fault diagnosis is a step-by-step process of accumulation. With the growth of expert knowledge and the continuing condition monitoring, the amount of information gradually increases, and the new failure mode often appears, thus an online fault diagnosis system where the diagnostic model can be updated in an incremental learning manner needs to be established. The online fault diagnosis system includes online monitoring of equipments operating status, online identification of failure modes and online updating of the diagnostic model. Online updating of the diagnostic model requires that the fault classifier can accurately identify the new failure mode by an incremental learning manner and the fault classifier could also be updated in real time to meet up with their classification performance.

Existing pattern recognition methods, such as Support Vector Machine (SVM) and Artificial Neural Network (ANN), require that the training samples are complete. Classifiers can only recognize the failure mode that already exists in the training phase. New samples must be combined with the original samples to re-train the fault classifier when there are new samples arriving. These traditional methods require that the system must store all the training samples and the training time has a rapid growth with the increase of training samples [1]. So it is difficult to achieve real time updating for classifier in online fault diagnosis.

Online intelligent fault diagnosis method is an important research direction in the industry and intelligent science field. Venkatasubramanian introduced application on online fault diagnosis based on pattern recognition [2–4]. Hidden Markov Model was presented to classify process data for on-line identifying abnormal operating conditions [5]. Li investigated online fault diagnosis method based on SVM [6]. However, in the aforementioned researches, many researchers only pay attention to online fault diagnosis of failure modes which are already existed in fault diagnosis classifier. But the class number in fault diagnosis is not constant. With new members enrolled, many failure modes that do not existed in the training phase appear, thus the class number is variable. Therefore, online fault diagnosis methods need to been investigated farther.

Incremental Support Vector Data Description (ISVDD) [7] overcomes shortages of the batch learning mode which exists in the traditional Support Vector Data Description (SVDD) [8] method. In ISVDD method, a priori model information and new training samples are used to update the classification model, knowledge of

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priori learning can be effectively used and repeated training time of the SVDD method could be reduced and the overall learning process can be cumulative [9]. ISVDD algorithm can quickly find the new failure mode in the continuous condition monitoring of the equipments, so it is widely used in abnormality detection of the equipments in the field of fault diagnosis.

As a fast learning algorithm for single hidden layer feedforward neural networks (SLFNs), Extreme Learning Machine (ELM) [10] is widely used in applications such as fault classification in series compensated transmission line [11], fault prognosis of mechanical components [12], computer aided diagnosis system [13], fault diagnosis on hydraulic tube tester [14], and so on. With the continuing condition monitoring, the class number of failure modes in fault diagnosis is not constant, Wang [15] proposed Dynamic Extreme Learning Machine (Dynamic ELM) which designs neural network with elastic output structure. Dynamic ELM can efficiently update itself when the number of output nodes has changes, so it has a good performance in applications with new members enrolled and obsolete members removed. Because the failure mode only increases in the fault diagnosis, Extreme Learning Machine with Incremental Output Structure (IOELM) is proposed in this paper, which is a simplified edition of Dynamic ELM.

New failure mode should be identified automatically and the classifier must be updated real-time in the online fault diagnosis system, so the ISVDD method is firstly used to detect the abnormal failure mode from new samples in this paper. If the failure mode existed in current fault model according to ISVDD, IOELM with fixed output structure is used to recognize the specific failure mode. When new failure mode is detected, the fixed structure is changed into an elastic structure by IOELM whose output nodes could be increased, then the new failure mode could be learned into the fault classifier and the real-time update of fault classifier is achieved effectively.

The remainder of this paper is organized as follows: ISVDD algorithm is reviewed in Section 2. Section 3 describes the proposed IOELM. Section 4 proposes online fault diagnosis process that is based on ISVDD and IOELM. Experiments on engine fault diagnosis are shown in Section 5. Section 6 draws conclusions and proposes future work.

2. Incremental Support Vector Data Description

SVDD is a kind of one-class classification algorithm which is based on the Support Vector Machine (SVM) theory. It uses kernel function to map input data into a higher dimensional space where the input data is described by a simple hyper-sphere boundary. So SVDD can be used for outlier detection effectively. However, it is difficult to get a perfect training set at the beginning of training in some real-world applications, the training data may arrive chunk-by-chunk or one-by-one, so it puts forward a new demand of the incremental learning ability to SVDD algorithm. SVDD is a representative batch learning method, its classification ability cannot be updated in an incremental learning manner, and so incremental learning methods [7,16–18] of SVM are extended to SVDD algorithm. Those modified algorithms inherit superiority of traditional SVDD algorithm, training time of the incremental samples is reduced evidently, and memory requirement of the optimization technique is decreased obviously. However, along with adding of new samples, non-support vector set in old samples may be converted into support vector, so classification accuracy will be affected if non-support vector set is discarded fast. In addition, some new samples which could be embodied by old samples need not to be learned repeatedly. So an Incremental Support Vector Data Description algorithm is proposed for online abnormality detection of mechanical equipments.

2.1. Review of SVDD

SVDD is an algorithm which uses support vectors to represent input data set, and it maps input data into a higher dimensional space where a closed boundary named hyper-sphere is established. Given input data $\{x|x_i \in \mathbf{R}^d, \quad i=1,2,\ldots,N\}$, to take into account possibility of outliers in the input data, distance from x_i to center of the sphere should not be strictly smaller than R^2 and larger distance should be penalized, so slack variables $\xi_i > 0$ are introduced. The error function to be minimized could be defined as:

$$F(R,a) = R^2 + C\sum_i \xi_i ||x_i - a||^2 \le R^2 + \xi_i \quad \forall i. \tag{1}$$

Subject to

$$||x_i - a||^2 \le R^2 + \xi_i \quad \forall i. \tag{2}$$

where α is center of the hyper-sphere, C is regularization parameter which controls trade-off between volume and errors, and R is radius of the hyper-sphere.

In order to constitute a flexible data description model, kernel function $K(x,y) = (\phi(x), \phi(y))$ is introduced. Where $(\phi(x), \phi(y))$ is dot product of $\phi(x)$ and $\phi(y)$. Among many kernels, the Gaussian kernel gives a closed data description $K(x,y) = \exp(-||x-y||^2/\sigma^2)$. Error function of SVDD using kernel function becomes

$$L = \sum_i \alpha_i K(x_i, x_i) - \sum_{i,j} \alpha_i \alpha_j K(x_i, x_j) \quad \forall \alpha_i : 0 \le \alpha_i \le C \tag{3}$$

where α_i is Lagrange multiplier.

Eq. (3) is a standard Quadratic Programming (QP) problem and the optimum α_i could be obtained using some optimization theories. In some real world applications, a great number of α_i are equal to zero, Tax [8] proposed that only a small quantity of points which present themselves on the boundary of hyper-sphere could be called support vectors. Radius of the hyper-sphere is distance from the center of hyper-sphere to support vector on the boundary. So a test object z is accepted when the distance is smaller or equal than the radius:

$$f(z) = K(z,z) - 2\sum_i \alpha_i K(z, x_i) + \sum_{i,j} \alpha_i \alpha_j K(x_i, x_j) \le R^2 \tag{4}$$

According to the optimization theory, the KKT conditions of the target function can be defined as

$$\alpha_i = 0 \Rightarrow ||x_i - a||^2 < R^2 \tag{5}$$

$$0 < \alpha_i < C \Rightarrow ||x_i - a||^2 = R^2 \tag{6}$$

$$\alpha_i = C \Rightarrow ||x_i - a||^2 > R^2 \tag{7}$$

As the aforementioned content, only objects with non-zero α_i are needed in the description and these objects are called support vectors of the description.

2.2. Theoretical analysis for incremental learning of SVDD

In the incremental learning scheme of the SVDD algorithm, the new samples $S' = \{x_i\}$ are not learned by the SVDD, so we defined the corresponding $\alpha_i = 0$, and then distance to center of the sphere has to be calculated. There are no new support vectors in the new samples S' when the distance is smaller than the radius. If new samples violate KKT conditions, new support vectors must exist in the new samples and non-support vector set in old samples may be converted into support vectors, so the non-support vector set should not be discarded entirely. A part of non-support vectors in