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A method of anomaly detection and fault diagnosis with online adaptive learning under small training samples

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ABSTRACT

Several methods of the modern intelligent anomaly detection and fault diagnosis have been developed to provide more efficient solutions. However, lacking of fault samples, the training stage and testing stage being mutually independent, and not recognizing new fault type restrict their application in some cases. This paper presents a method of anomaly detection and fault diagnosis with online adaptive learning under small training samples. This approach has classification function and clustering function at the same time. The samples of known fault type are categorized and the samples of unknown fault type are clustered with this approach. To determine the performance and possible advantages of the approaches, the experiments on ball bearing fault data and Iris data were performed. Results show that our proposed approach outperforms the other methods, when the training samples are inadequate to cover all of the fault types. The less the known fault types are, the more advantages it has. To a certain extent, this approach could make up for the disadvantages of other methods of anomaly detection and fault diagnosis.

1. Introduction

The intelligent anomaly detection and fault diagnosis methods are significant for improving the safeness and reliability of equipment, and reducing economic loss because of failure shutdown [1,2]. Currently, several methods of the modern intelligent anomaly detection and fault diagnosis, such as neural networks [3,4], support vector machines (SVM) [5,6], fuzzy theory [7], and rough sets theory [8,9], have been developed to provide more efficient solutions. But there are still some difficult problems remaining to be solved [10].

(1) Lacking of fault sample is a knotty problem in the fault detection of the mechanical equipment. However, most of the modern intelligent anomaly detection and fault diagnosis algorithms depend on a large number of samples which are not easy to implement, because of the difficulty of obtaining fault samples in the actual production. But a large number of normal samples are easy to obtain.
(2) The training stage and testing stage of these algorithms are mutually independent, and they lack continuous learning ability. The fault diagnosis methods establish the mapping between unknown samples and fault types. On the one hand, these models can not find new fault type, because all the types of failure can not be obtained at one time in the actual production. On the other hand, the fault detection models generated are only appropriate to the special training data. Once the equipment operation condition changes, they cannot work as well as before, unless retrained.

Artificial immune system (AIS) is a new type of adaptive system that is inspired by the biological immune system (BIS) [11,12]. AIS solves the real world problems by simulating the functions, principles and model of BIS. Currently, artificial immune algorithms inspired by negative selection [13–15], clone selection [16,17], immune network [18] and danger theory [19], have been developed to provide more efficient solutions, including anomaly detection [20–22], fault diagnosis [23,24], computer security [25,26], classification [27,28], clustering [29] and optimization [30,31].

Negative selection algorithm (NSA) is one of the AIS algorithms that are widely in use [11,14]. NSA was proposed by Forrest [13]. It is inspired by the mechanism of T-cell maturation that happens in the thymus. As a one-class classification algorithm, it has attracted widespread interest in the field of anomaly detection [11,12]. The initial NSA used binary encoding to represent self and non-self samples [13]. Later, the real-valued NSA (RNSA) was presented [11,14]. In order to make RNSA easier to understand, some basic concepts are introduced as follows [32,33], and these terms are described in 2-dimensions space as shown in Fig. 1.

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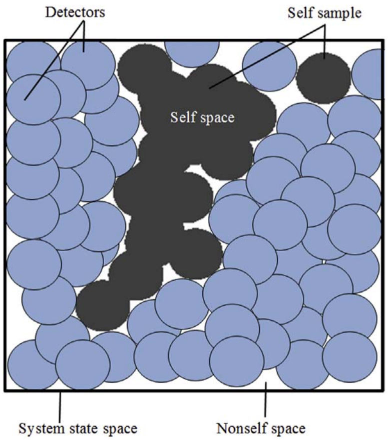

Fig. 1. The terms are described in 2-dimensions space.

(1) System state space $\boldsymbol{T}$: A state of the system can be represented by a vector of features $\boldsymbol{t}^i=[t^i_1,t^i_2,...,t^i_n]$, $\boldsymbol{T}=\{\boldsymbol{t}^i,i=1,2,...,u\}\subset\boldsymbol{R}^n$. For simplicity, it is assumed that each feature is normalized to [0,1], and $\boldsymbol{T}=[0,1]^n$.
(2) Self space $\boldsymbol{S}$: A set of feature vectors represents the normal state of the system, $\boldsymbol{S}=\{\boldsymbol{s}_i,i=1,2,...,k\}\subset\boldsymbol{T}$.
(3) Nonself space $\boldsymbol{N}$: The complement space of self space is called nonself space. Where $\boldsymbol{T}=\boldsymbol{S}\cup\boldsymbol{N}$, and $\boldsymbol{S}\cap\boldsymbol{N}=\emptyset$.
(4) Self sample $\boldsymbol{s}$: $\boldsymbol{s}=\{<\boldsymbol{s}_i, r_s>|\boldsymbol{s}_i\in\boldsymbol{S}, r_s\in\boldsymbol{R}\}$, where r_s is the self radius.
(5) Detector $\boldsymbol{d}$: $\boldsymbol{d}=\{<\boldsymbol{d}_i, r_d>|\boldsymbol{d}_i\in\boldsymbol{N}, r_d\in\boldsymbol{R}\}$, where r_d is the radius of detector.

Interface detector (I-detector) and Boundary-Fixed Negative Selective Algorithm (FB-NSA) are novel negative selection algorithms for anomaly detection [33,34]. I-detector is one or more closed hypersurfaces, which is generated by training normal samples and described by boundary samples, the position information of boundary samples, and the radius of training samples. Non-self samples are outside of I-detector, and self samples are in the other side of I-detector. I-detector can surround the self space with an appropriate self radius r_s. FB-NSA generates a layer of detectors, which are around the self space. Self samples are on one side of the detectors, and non-self samples are on the other side of detectors or within detectors. I-detector and FB-NSA carry out the learning process during the testing stage to adapt itself to real-time change of self space.

The false alarm rate decreases with the increasing of the number of training samples, and I-detector and FB-NSA are no exception. We cannot obtain enough data for training within one time, but interface detector with online adaptive learning under small training samples (OALI-detector) and boundary-fixed negative selection algorithm with online adaptive learning under small samples (OALFB-NSA) can solve this problem. OALI-detector and OALFB-NSA can adapt themselves to real-time change of self space during the testing stage, and can obtain the higher detection rate and lower false alarm rate, even if only one self sample is used for training. However, the detection rate of OALFB-NSA is lower than that of OALI-detector, and OALFB-NSA is more likely to cause overfitting than OALI-detector [33,35].

The I-detector and the learning progress of OALI-detector in $[0,1]^2$ is shown in Fig. 2. There are 41 training samples and 2 testing samples in Fig. 2(a). The I-detector generated by training samples is shown in Fig. 2(b), and it is described by 22 boundary samples. The I-detector recognizes $\boldsymbol{t}_1$ is a self sample and $\boldsymbol{t}_1$ is a new boundary sample, $\boldsymbol{t}_2$ is a non-self sample (shown in Fig. 2(c)). $\boldsymbol{t}_1$ makes the I-detector to adapt itself as a new I-detector (shown in Fig. 2(d)). The automatic adjustment process of I-detector is the learning process of OALI-detector.

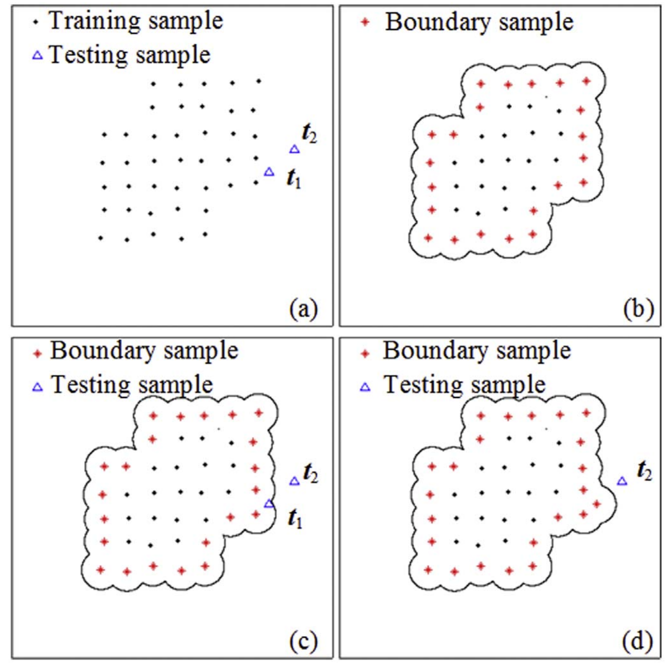

Fig. 2. I-detector and the learning process of OALI-detector.

The boundary samples which are used for describing I-detector is a subset of training samples, so I-detector is an effective method to reduce the data.

I-detector and OALI-detector are inspired by negative selection mechanism, and they are one-class classification algorithm for anomaly detection. However, the fault diagnosis problems can be stated as a multi-classification problem in general. So I-detector and OALI-detector will require extending their functionalities to solve multi-classification problems.

The existing fault diagnosis methods usually extract feature of fault data, and establish the mapping between unknown data and fault types, and I-detector and OALI-detector are no exception. Nevertheless, all types of fault data can not be obtained at once in the practical production. Most of the classifiers can not recognize the samples of new fault type. So I-detector and OALI-detector will require extending their functionalities to recognize the samples of new fault type.

I-detector and OALI-detector have the function of reducing data. However, when the boundary of self space is complex, the number of boundary samples is large, which leads to low detecting efficiency. So I-detector and OALI-detector will require extending their functionalities to improve detecting efficiency.

These issues restrict the application of I-detector and OALI-detector. Therefore, the paper presents a method of anomaly detection and fault diagnosis with online adaptive learning under small training samples. This approach is a fusion method of anomaly detection and fault diagnosis, and is proposed based on extension and supplement of the I-detector and OALI-detector. This approach has classification function and clustering function at the same time. It categorizes the samples of known fault types and clusters the samples of unknown fault types. We call this idea and the algorithm based on it as adaptive hyper-ring detector (AHr-detector).

The remaining sections of the paper are structured as follows: the model of AHr-detector is presented in detail in Section 2. The experimental results are presented in Section 3. In Section 4, conclusions are provided.