Engineering Applications of Artificial Intelligence 50 (2016) 93–105

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

A boundary-fixed negative selection algorithm with online adaptive learning under small samples for anomaly detection

Dong Li [a,b], Shulin Liu [a,*], Hongli Zhang [a]

[a] School of Mechatronics Engineering and Automation, Shanghai University, Shanghai 200072, China
[b] School of Petroleum Engineering, Changzhou University, Changzhou 213164, China

ARTICLE INFO

Article history:
Received 27 January 2015
Received in revised form
21 September 2015
Accepted 29 December 2015

Keywords:
Artificial immune system
Negative selection algorithm
Anomaly detection
Online adaptive learning

ABSTRACT

The traditional negative selection algorithm (NSA) lacks online adaptive learning ability, and this restricts its application range. A new NSA, boundary-fixed negative selection algorithm with online adaptive learning under small samples (OALFB-NSA), is proposed in this paper. Boundary-fixed negative selection algorithm (FB-NSA) generates a layer of detectors, which are around the self space. These detectors are only related to the training samples, and have nothing to do with the training times. OALFB-NSA detectors can adapt themselves to real-time variety of self space during the testing stage. Experimental comparison among FB-NSA, V-detector and other anomaly detection algorithms on Iris data sets and biomedical dataset shows that the FB-NSA can obtain the higher detection rate and lower false alarm rate in most cases. The experimental comparison between OALFB-NSA, interface detector with online adaptive learning under small training samples (OALI-detector) and V-detector on Iris data sets shows that when overfitting does not occur, the OALFB-NSA can obtain the higher detection rate and lower false alarm rate, even if only **one** self sample is used for training.

1. Introduction

In recent years, more and more researchers have been attracted to the field of Artificial Immune System (AIS) to develop new algorithms, which are inspired by the natural immune system mechanism (Dasgupta et al., 2011; Muhamad and Deris, 2013; Yang et al., 2014). Currently, major types of AIS algorithms such as negative selection, clone selection and immune network, have been developed in the literature (Carter, 2000; De Castro and Von Zuben, 2000; Farmer et al., 1986; Gong et al., 2008; Gonzalez et al., 2002). These algorithms provide more efficient results for problems including anomaly detection (González and Dasgupta, 2003; Idris et al., 2015), fault diagnosis (Dai and Zhao, 2011; Gao et al., 2013; Ghosh and Srinivasan, 2010) and optimization (Delibasis et al., 2011; Leão et al., 2010; Li et al., 2011; Zhong and Zhang, 2013). Negative Selection Algorithm (NSA) is one of the AIS algorithms that are widely in use (Dasgupta et al., 2011; Ji and Dasgupta, 2007). NSA was proposed by Forrest et al. (1994). 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 field of anomaly detection (Chen, 2013; Mohammadi et al., 2013; Zhang et al., 2013). Many modified versions of NSA are also being proposed (Chen et al., 2014; Mahapatra et al., 2013; Zhang et al., 2010).

The detector coverage is an important aspect of NSA. Many works have focused on improving the detector coverage and reducing the detector number. The boundary detectors are allowed to cover a part of self space. Therefore, it can eliminate the holes on the boundary and can detect the deceiving anomalies hidden in the self space (Wang et al., 2011). FtNSA generates self-detectors to cover the self space and generates V-detectors to cover the non-self space respectively in the training stage. It can reduce computational cost in testing stage, and can also improve the self space coverage (Gong et al., 2012). The feature space is divided into a number of grid cells by GF-RNSA, and then detectors are separately generated in each cell. As candidate detectors just need to compare with the self antigens located in the same cell rather than with the whole self set, the detector training can be more efficient (Chen et al., 2014). The particle swarm optimization is implemented to improve the random detector generation in the negative selection algorithm by NSA-PSO. It can improve the traditional random generation of detectors in the real value negative selection algorithm and optimize the generated detectors at the same time (Idris et al., 2015).

Although the methods mentioned above can improve the detector coverage and detection rate, little attention has been paid to the detector with online adaptive learning under small training samples. For training data are just from partial self samples and

* Corresponding author. Tel.: +86 21 56331523.
E-mail address: lsl346@shu.edu.cn (S. Liu).

http://dx.doi.org/10.1016/j.engappai.2015.12.014
0952-1976/

the self space often varies with time. The generated detectors are only appropriate to special training data. If the self space changes, the detectors cannot work as well as before, unless retrained. Interface detector (I-detector) can carry out the learning process during the testing stage to adapt itself to real-time change of self space (Li et al., 2015). However, its testing algorithm indicates that it seems to belong to positive selection algorithm (PSA) than NSA (Esponda et al., 2004; Stibor et al., 2005).

The paper presents a novel negative selection algorithm named as boundary-fixed negative selective algorithm with online adaptive learning under small samples (OALFB-NSA). Boundary-fixed negative selective algorithm (FB-NSA) generates a layer of detectors, which are around the self space. Self samples are in one side of the detectors, and non-self samples are in the other side of detectors or within detectors. The FB-NSA detectors are generated in non-random ways, and the position, size and quantity of FB-NSA detectors are constant. These detectors are only related to the training samples, and are irrelevant to the training times. In addition, during the testing stage, OALFB-NSA can be adapted to real-time change of self space, even if only one self sample is used for training.

The remaining sections of the paper are structured as follows: the models of FB-NSA and OALFB-NSA are presented in detail in Sections 2 and 3, respectively. The experimental results are presented in Section 4. In Section 5, conclusions are provided.

2. Boundary-fixed negative selection algorithm (FB-NSA)

2.1. The implementation of FB-NSA

The detectors of NSA are generated at random, the detectors of real-valued NSA (RNSA) is no exception. The RNSA detectors which are around the self space can be generated easily, but they cannot be directly used for anomaly detection. It is easy to calculate the distance between a detector and a testing sample, but it is difficult to confirm the position relationship between them. Therefore, these detectors can not recognize what side of detectors the testing sample is on.

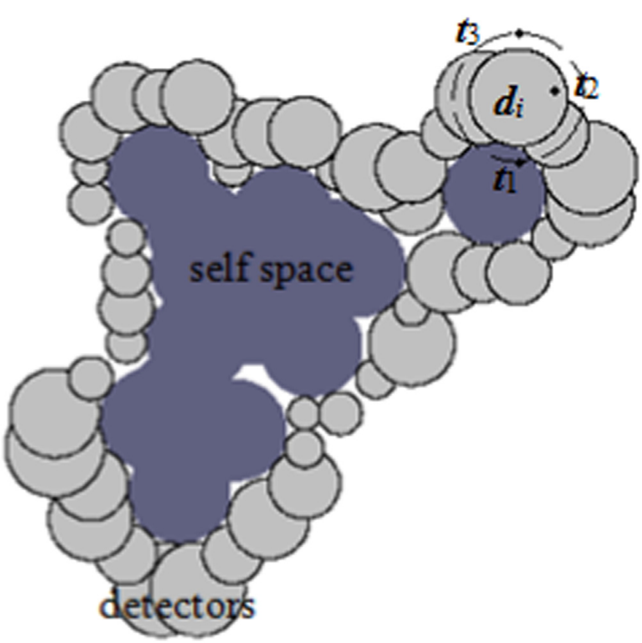

Fig. 1. FB-NSA detectors.

The FB-NSA detectors are described in $[0,1]^2$ shown in Fig. 1. The dark gray part of the space is self space, and the other part of the space is non-self space. There are 45 FB-NSA detectors around the self space. As shown in Fig. 1, $\boldsymbol{t}_1$ belongs to self space and it is a self sample, marked as $\boldsymbol{t}_1 \in \boldsymbol{S}$; $\boldsymbol{t}_2$ and $\boldsymbol{t}_3$ belong to non-self space, and they are non-self samples, marked as $\boldsymbol{t}_2 \in \boldsymbol{N}$, $\boldsymbol{t}_3 \in \boldsymbol{N}$. $\boldsymbol{t}_1 \in \boldsymbol{S}$, and it is in one side of these detectors. $\boldsymbol{t}_3 \in \boldsymbol{N}$, and it is in the other side of these detectors. $\boldsymbol{t}_2 \in \boldsymbol{N}$, and it is in the detector d_i. When the testing algorithm of the traditional RNSA is used in this case, $\boldsymbol{t}_2$ is covered by the detector d_i, $\boldsymbol{t}_2$ is a non-self sample, $\boldsymbol{t}_2 \in \boldsymbol{N}$ (right). $\boldsymbol{t}_1$ and $\boldsymbol{t}_3$ are not covered by the detector d_i, $\boldsymbol{t}_1$ and $\boldsymbol{t}_3$ are self samples, $\boldsymbol{t}_1 \in \boldsymbol{S}$ (right), $\boldsymbol{t}_3 \in \boldsymbol{S}$ (wrong).

To sum up, the FB-NSA detector can be defined as:

Definition 1. *FB-NSA detector*, $D = \{ <\boldsymbol{d}_i, r_i, p_i> \mid \boldsymbol{d}_i \in \boldsymbol{R}^n, r_i \in \boldsymbol{R} \}$

where $\boldsymbol{d}_i$ is the center of FB-NSA detector, r_i is the radius of $\boldsymbol{d}_i$, $r_i = d - r_s$, d is the distance between $\boldsymbol{d}_i$ and its the nearest training sample, r_s is the radius of training sample, $_{pi}$ is the position information of $\boldsymbol{d}_i$.

It is difficult to confirm the position relationship between two hypershperes, but it is easy to confirm the position relationship between two hypercubes. If the non-self space is filled with same hyercubes, the non-self space can be approximated with Eq. (1).

$$V_{Nonself} = \lim_{V_{hypercube} \to 0} \sum_{i=1}^{\infty} (V_{hypercube})_i \tag{1}$$

Fig. 2 shows the approximation progress in 2-dimensional space. There are 40^2, 80^2, 160^2 squares in Fig. 2(a), (b) and (c), respectively. It is clear that the boundary of squares in the non-self space can be approximated to the boundary of non-self space.

Therefore, the FB-NSA detectors can be generated with the hypercubes which are close to the self space. The center of the hypercube is the center of the detector, and the position relationship between the two hypercubes is the position relationship between the two detectors. These hypercubes are defined as boundary hypercubes, and every boundary hypercube generates a FB-NSA detector.

The key to generate FB-NSA detector is to obtain the boundary hypercubes. To obtain boundary hypercubes, the state space $\boldsymbol{T}$ should be evenly divided into m^n hypercubes:

$$\boldsymbol{T} = \cup_{i=1}^{m^n} h_i, \tag{2}$$

where m is the number of segments of each dimension and n is the number of space dimension.

Definition 2. *Empty hypercube* and *non-empty hypercube*, when a hypercube h_i is covered by a self sample or a self sample located in h_i, it is a non-empty hypercube, marked as $h_i = \Theta$. Otherwise it is an empty hypercube, marked as $h_i = \text{O}$.

It is complicated to determine whether a hypercube is covered by self sample through calculation. To simplify the algorithm, a definition, recognition radius δ, is proposed.

Definition 3. *Recognition radius* δ, δ is a pre-set distance and

$$f(h_i) = \begin{cases} \Theta & d \le \delta \\ \text{O} & d > \delta \end{cases} \tag{3}$$

where d is the distance between $\boldsymbol{c}_i$ and training sample $\boldsymbol{s}_j$ and $\boldsymbol{c}_i$ is the center of hypercube h_i.

Recognition radius δ is an important parameter to determine the property of the hypercube. According to Definition 3, whether a hypercube is empty is determined according to the distance between its center and self sample. It is clear that to obtain all the