Water Mine Model Recognition by Immune Neural Network

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Abstract. An immune neural network (INN) is proposed for water mine model recognition. The INN is a two-layer Boolean network whose number of outputs is adaptive according to the task and the affinity threshold. The precision of the recognition results can be controlled through adjusting the affinity threshold. The INN has favorable capability of noise tolerance.

Keywords: water mine model, recognition, immune neural network.

1 Introduction

It is necessary for mine countermeasure systems to recognize the model of a water mine. Most of the previous researches on mine countermeasures [1][2][3] focused main attentions on the detection and classification of water mines. But the previous approaches can only classify the detected object as two classes, i.e., mine-like or not. In this paper, an immune neural network (INN) is constructed based on a modified clonal selection operation for water mine model recognition.

2 Immune Neural Network

Represent the feature data of water mines as an antigen population $A^g = \{A^g_1, A^g_2 \dots A^g_n\}$. An antigen can be represented as l -length bit string. Each bit represents a feature. The antibody repertoire, $A^b = \{A^b_1, A^b_2, \dots, A^b_m\}$, will be modeled as a Boolean competitive network with l inputs, called INN. Employ an l -dimensional vector w_j represents the weights connecting the inputs to the output unit j . Define the affinity A_{ij} as the Hamming distance between A^g_i and A^b_j . For each A^g_i , v_i indexing the highest affinity antibody. The antigens concentration c_j for A^b_j can be calculated according to Eq.(1),

$$c_j = \sum_{i=1}^n \text{iif}(v_i = j, 1, 0), \quad (1)$$

where, $\text{iif}(v_i = j, 1, 0)$ means that if $v_i = j$ holds then return 1 else 0. Define e as an affinity threshold. For A^g_i and A^b_j , if $l - A_{ij} > e$ then we can say that A^g_i and A^b_j are

matched. Define m_j as an affinity maturation indicator. If m_j is *True* then stop cloning antibody A_j^b . For antibody A_j^b and arbitrary $i \in \{i \mid v_i = j\}$, if $l - A_{ij} > e$ holds, then set $m_j = \text{True}$ as Eq.(2),

$$m_j = \bigwedge_{i \in \{i \mid v_i = j\}} (l - A_{ij} > e). \quad (2)$$

We developed a modified clonal selection algorithm for constructing an INN:

- 1) Initiate an INN with n antigens $A_1^g, A_2^g \dots A_n^g$ and 1 antibody A_1^b . For each integer $i \in [1, n]$, set $v_i = 1$. Set each bit of w_i to 1. Set $c_1 = n$, $m_1 = \text{False}$. Set e to an appropriate value.
- 2) Determine the candidate A_j^b to be cloned according to Eq.(3). If j is *null* then stop else continue step 3) to clone A_j^b .

$$j = \arg \max_{j \in O} c_j, \text{ where } O = \{j \mid c_j > 1 \wedge m_j = \text{False}\} \quad (3)$$

- 3) Select the worst matching A_i^g of A_j^b according to Eq.(4),

$$i = \arg \min_{i \in \{i \mid v_i = j\}} A_{ij}. \quad (4)$$

- 4) Clone a new antibody A_k^b with the weights w_k of its antibody are the exact complement of A_i^g , then add A_k^b to INN.
- 5) For each antigen A_i^g , update v_i . For each antibody A_j^b , update c_j and m_j .
- 6) If all antibodies are mature then delete the antibodies with $c=0$ and stop, else goto step 2).

When the algorithm (MCSA for short) stops, an INN is constructed, each output of which represents one or several antigen patterns, i.e., water mine models. The number of patterns that an output represents is determined by the affinity threshold e . When $e = 0$, one output corresponds to one pattern. The bigger the value of e is, the more patterns an output represents along with the lower precision.

The process of recognition is very simple. Given an antigen A_i^g as input, the INN computes the antibody being activated according to Eq.(5), then the water mine model can be recognized.

$$j = \arg \max_{j \in O} A_{ij}, \text{ where } O = \{j \mid l - A_{ij} > e\} \quad (5)$$

There is no output can be activated if $O = \Phi$, which means that A_i^g cannot be recognized, i.e., the water mine is not any known model or may be it is not a water mine at all.

3 Simulation Experiments

For constructing an INN, a water mine data set with models and binary attributes was prepared as shown in Table 1. We applied MCSA to the data set with setting $l=20$, $n=21$, and $e=0$, which means that the MCSA will create a network with antibodies highly specific for each input pattern (antigen). Thus, it would be expected that the

final network was composed of 21 antibodies, but the resultant network contained only 18 antibodies. This is because that the models (e.g., NM103 and WSM210) mapped into the same node are described as the same attribute strings.

Table 1. Water mine data set with their models and binary attributes

	PLARM-1A	PDM-1B	PDM-2B	PDM-1M	PDM-3YA	U/I	MAS/17	MAS/22	VS-RM-30	NM102	NM103	DUM101	DUM102	STORM	WSM110	WSM210	M89A2	MK60	MK65	MK67	MISHM
Shape																					
hemisphere	0	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
cylinder	0	0	1	0	0	0	0	0	0	1	0	1	0	1	1	0	0	1	1	1	1
truncated-cone	0	1	0	0	0	0	0	0	0	0	1	0	1	0	0	1	0	0	0	0	0
oblate	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0
clutter	1	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Color																					
green	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
black	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
gray	0	0	0	0	0	0	0	1	1	1	1	0	0	1	1	1	1	1	1	1	0
red	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
orange	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0
yellow	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
brown	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
State																					
floating	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
moored	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1
bottom	0	1	0	0	0	0	0	1	1	0	1	0	1	0	1	1	0	0	1	1	0
navigation	0	0	0	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0	0	0	0
adsorption	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Depth																					
deep	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	1	1	1	1
shallow	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0
Has																					
antennae	1	1	1	1	1	1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0

In most cases, the sensor data may be incomplete or inaccurate. The INN can easily deal with these cases by adjusting the value of the affinity threshold e when recognizes, which can be demonstrated by the following experiments. Random noise was inserted into the learning samples in Table 1 by simply reverting a bit 0 into a 1, or vice-versa. We tested eleven different noise levels from 0% to 50%, corresponding to the shift of 0 to 10 bits, respectively. The INN was tested for different values of the affinity threshold e from 0 to 10, and a correct recognition (CR) is assumed when the network maps the corrupted pattern into the same node as the original pattern. Fig.1 depicts the experiment results that are the average taken over ten runs. Fig.1 shows that the CR is affected both by the number of noise bits and the affinity threshold e . Keeping a value of e constant, the CR decreases almost linearly with the noise level increasing. If we keep a constant noise level, the CR increases nonlinearly, i.e., the CR almost keeps constant when the value of e is bigger than the number of noise bits.

In these experiments, we did not take into account the effect of adjusting the affinity threshold e when the INN is constructed. Apparently, the value of e in recognition should be equal to or bigger than that in construction. It is an acceptable strategy to set e in recognition to a bigger value when the noise level is uncertain.

Fig. 1. The correct recognition rate of INN

4 Conclusions

The INN is a two-layer Boolean network whose number of outputs is adaptive according to the task and the affinity threshold, which is significant for solving machine-learning problems, such as knowledge acquisition and classification. The precision of recognition result can be controlled through adjusting the affinity threshold, which endows INN with satisfied noise tolerance capability. In the future, we will apply the INN to underwater minesweepers.

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