A Dynamic Approach to Artificial Immune Systems utilizing Neural Networks

Stefan Schadwinkel
Chemnitz University of Technology
09107 Chemnitz, Germany
schas@hrz.tu-chemnitz.de

Werner Dilger
Chemnitz University of Technology
09107 Chemnitz, Germany
wdi@hrz.tu-chemnitz.de

ABSTRACT

The purpose of this work is to propose an immune-inspired setup to use a self-organizing map as a computational model for the interaction of antigens and antibodies. The proposed approach may be used as a part in other immune algorithms, or can possibly be used to detect anomalies in time series data.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search—*heuristic methods*;
I.6 [**Simulation and Modeling**]: Miscellaneous

General Terms

Algorithms, Theory

Keywords

artificial immune system, artificial intelligence, neural networks, online algorithms, process monitoring, self-organizing map

1. INTRODUCTION

This work proposes the idea that a self-organizing map [1] can be seen as an embodiment of a system's body. It exists in an environment and additionally reinforces its own structure from "within". The interaction or interference between the stimuli from the environment and the internal reinforcement is represented by the topology of the emerging structure represented by the weights of the SOM. This interaction is interpreted from an immune viewpoint as the monitoring and controlling of the interaction of a biological body and the substances/cells that get into it. This is the core purpose of the immune system with the aim to ensure the body's proper functioning.

To expose the SOM to both external stimuli and internal reinforcement, it is trained resp. modified by two independent input streams. In addition, the SOM weights are monitored and analysed to gain information about the interaction of both input streams. This can be used to detect anomalies within one input stream in respect of the other stream. An anomaly is thus not absolute but relative to the other stream. Once an anomaly is detected, actions can be taken against it within the environment and the map may have to be readjusted to allow subsequent detections.

This conforms to both the self-assertion vision [2] and to the danger theory [3] as there is no imposed duality on the actual input patterns and the danger signal (or anomaly condition signal) is detected by referencing to the system's "self".

The proposed system does not implement the adaption of the immune reaction to external stimuli, only sustaining and detection mechanisms.

The proposed setup of the system will be refered to as IS-SOM for "Immune System on SOM". It is outlined in section 2 and the mapping to immune concepts is further explained in section 3.

GECCO'06, July 8–12, 2006, Seattle, Washington, USA.
ACM 1-59593-186-4/06/0007.

2. THE IS-SOM SETUP

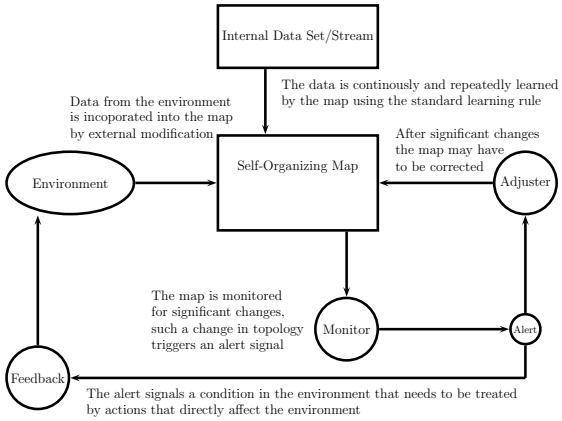

Figure 1: Setup of the IS-SOM

2.1 The Environment

The environment provides the data patterns which are to be monitored and in which anomalies shall be detected.

To incorporate the patterns into the weights of the SOM, the SOM learning rule can be used. In this case the parameters of the learning algorithm can be different from the parameters used with the internal data.

Alternatively, the patterns can simply be added to the corresponding best matching units. This has interesting effects which are explained in section 2.3 together with a short comparison to using the learning rule.

2.2 The Internal Data Set/Stream

The internal data consists of a set or stream of data patterns which represents the supposed internal structure. Its patterns are learned by the SOM using the SOM learning rule. In case of a data set, the patterns to learn are chosen randomly from the set, in case of a stream, they are learned in sequence.

To use the IS-SOM setup to detect anomalies, this data set or stream would represent anomaly-free or "normal" data.

2.3 The Self-Organizing Map

The central role of the system is the SOM. It is initialized by allowing it to adapt to the internal data.

After the map is sufficiently organized, data patterns from the environment are incorporated into the map's structure while the learning of the internal samples continues.

If both input streams are applied to the map using the SOM learning rule, all changes in the structure of the map emerge through the process of self-organization. By that, changes will be relatively "smooth" and anomaly conditions will be relatively subtle. This can be intensified by using a higher learning rate and/or larger neighbourhood radius, but still great care has to be taken to get a resonably small false positive rate.

The other way, to apply the patterns from the environment by addition to the corresponding best matching units seems to be more promising. An advantage of this way of modifying the map can be achieved when the co-domain of the input vectors is bounded. If one pattern is applied often in a short time span, the learning of the internal data will not be fast enough to cancel its impact completely. As the pattern is repeatedly added to one and the same unit, its weight vector will transgress the boundary of the co-domain (given that the data type used for implementation allows for this) and the next time, the weight vector of one of the neighbour units will have a lower distance to the input pattern than its original best matching unit. By reiteration of that process, more and more units of the map are influenced by this often repeated input vector.

This will create a detectable distortion in the map's structure and once this distortion becomes too intense, an anomaly condition can be assumed.

2.4 The Monitor

The monitor tracks the position and size of the main clusters in time. Once the size and/or position of one or more clusters changes too much in a given time span, an alert signal is triggered.

A more complex anomaly condition would be a change in the relative positions of the clusters.

2.5 The Alert Signal

The alert signal tells the adjuster and the feedback mechanism that an anomaly condition has been reached. With the signal, specific information can be relayed. This can include a value that indicates the strength of the alert based on the degree of change in the topology of the map. In addition, there can be different types of alerts based on the compromised clusters.

As the alert signal is generated based on an internal change in relation to itself, the model conforms to the main idea of the danger theory [3].

2.6 The Adjuster

The adjuster restores the map's regular topology based on the alert signal. This can be done by reinitializing the map with random values and allowing a certain learning time without input from the environment or by restoring the state of the map prior to the detection of the anomaly.

2.7 The Feedback to the Environment

The feedback mechanism is responsible for dealing with the detected anomaly within the environment. Once the conditions in the environment are treated, the incorporation of patterns from the environment into the map can be resumed and subsequent anomalies can be detected.

3. IMMUNE CONCEPTS AND THE SOM

The IS-SOM setup can be considered to be a hybrid neuro-immune approach, merging immune ideas with the model of self-organizing maps.

The mapping of immune elements to the proposed setup can be seen as follows: Internal data patterns are considered as antibodies (Ab), patterns from the environment as antigens (Ag). The SOM itself provides an environment for the Ab-Ag interaction. The matching of antigens to antibodies is based on similarity and happens due to the determination of the best matching unit in the SOM.

If the patterns from the environment positively reinforce the structure caused by the internal data within the SOM, the immune system is optimally trained. If the patterns from the environment negatively act on the SOM structure, then the immune system would have to adapt its antibodies to better represent the external patterns. For the proposed system, this means that the internal data set would have to be changed. But because the suggested usage is detection of such occurences and not adaption, the causality is inverted: in case something "special" is encountered, it has to be taken care of in the environment.

4. CONCLUSIONS

Neural networks and artificial immune systems provide interesting concepts that may be beneficially combined. Since the proposed setup is different from other approaches to use the SOM or neuro-immune techniques for anomaly detection, like those described in [4], possible applications and performance should be investigated by further research.

5. REFERENCES

[1] **Kohonen, Teuvo (1997):**
Self-Organizing Maps, Second Edition, *Springer*

[2] **Bersini, Hugues (2002):**
Self-Assertion versus Self-Recognition: A Tribute to Francisco Varela, *Université Libre des Bruxelles, IRIDIA-CP 194/6, ICARIS 2002*

[3] **Aickelin, Uwe, Cayzer, Steve (2002):**
The Danger Theory and Its Application to Artificial Immune Systems, *HP Laboratories Bristol, HPL-2002-244*

[4] **González, Fabio A., Dasgupta, Dipankar (2002):**
Neuro-Immune and Self-Organizing Map Approaches to Anomaly Detection: A comparison., *In the proceedings of the First International Conference on Artificial Immune Systems UK, September 9-11, 2002*