Immune-Based Optimization of Predicting Neural Networks

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Abstract. Artificial immune systems turned out to be an interesting technique introduced into the area of *soft computing*. In the paper the idea of an immunological selection mechanism in the agent-based optimization of a neural network architecture is presented. General considerations are illustrated by the particular system dedicated to time-series prediction. Selected experimental results conclude the work.

1 Introduction

Looking for solutions for many difficult problems, researchers very often turned to the processes observed in nature. Such biologically and socially inspired computational models were successfully applied to various problems and they still belong to a very important research area of *soft computing*. Artificial neural networks, which principles of operation originate from phenomena occurring in the brain, evolutionary algorithms based on the rules of organic evolution, multi-agent systems originating from the observation of social processes are the examples of such approaches. Also artificial immune systems, inspired by the human immunity, recently began to be the subject of increased researchers' interest. Such techniques are often combined together to create hybrid systems, that by the effect of synergy exhibit some kind of intelligent behaviour, which is sometimes called *computational intelligence* as opposed to rather symbolic artificial intelligence [1].

Following this idea a hybrid optimization technique of evolutionary multi-agent systems have been applied to a wide range of different problems [8]. In this paper immunological mechanisms are proposed as a more effective alternative to classical energetic ones used in EMAS. Particularly the introduction of *negative selection* may lead to early removing of improper solutions from the evolving population, and thus skip the process of energetic evaluation [7] and speed up the computation. Such approach may be justified in specific cases of the problems, that require relatively time-consuming fitness evaluation. As an example of such a problem the optimization of neural network architecture is considered in the paper.

Fig. 1. Negative selection mechanism in artificial immune systems

Below, after a short presentation of the basics of human immunity and artificial immune systems, the details of the proposed approach are given. First the idea of neural multi-agent system for time-series prediction is described. Then the application of immune-based selection mechanism in agent-based neural network architecture optimization system is proposed. Some preliminary results obtained for a typical simple prediction problem allow for the first conclusions to be drawn.

2 Artificial Immune Systems

An immune system plays a key role in maintaining the stable functioning of the human body. At the cellular layer lymphocytes are responsible for detection and elimination of disfunctional endogenous cells, termed infectious cells and exogenous microorganisms, infectious non-self cells such as bacteria and viruses. One of the most important adaptation mechanisms in the human immunity is based on the process of negative selection, which allows for removal of lymphocytes that recognize self cells [5].

Different approaches inspired by the human immune system were constructed and applied to enhance algorithms solving many problems, such as classification or optimization [12]. Basic principles of immune-based algorithms utilising negative selection may be clearly illustrated on a classical problem of machine learning – concept learning – as described below.

Concept learning can be framed as the problem of acquiring the definition of a general category given a sample of positive and negative training examples of these categories' elements [10]. Thus the solutions can be divided into

Fig. 2. A single predicting neural network (a) and the whole multi-agent system (b)

two groups: self (positive) and non-self (negative). An artificial immune system, which consists of a large number of lymphocytes can be trained to recognize these solutions in the process of negative selection. In the beginning the lymphocytes are created, but at this point they are considered immature. Next, the affinity binding of these cells to present self-cells (good solutions of some problem) is evaluated. Then the lymphocytes that bind themselves to "good" cells are eliminated. Finally, lymphocyte-cells that survive entire process are considered mature (see fig. 1). Mature lymphocytes are presented with the cells that have unknown origin (they may be self, or non-self cells), and they are believed to have possibility of classifying them [11].

3 Neural Agents for Time-Series Prediction

Prediction (or *forecasting*) is a generation of information about the possible future development of some process from data about its past and present behaviour. Time-series prediction consists in searching for some trends in the sequence of values of some variable [6].

Many examples from the literature show that neural networks may be successfully used as a mechanism to model the characteristics of a signal in a system for a time-series prediction [9]. The choice of a particular architecture of the network is to a large extent determined by a particular problem. Usually the next value of the series is predicted on the basis of a fixed number of the previous ones. Thus the number of input neurons correspond to the number of values the prediction is based on, and the output neuron(s) give prediction(s) of the next-to-come value(s) of the series. The multi-layer perceptron (MLP) in (see fig. 2a) should predict t_{n+1} value of the series, basing on some previous values, which are given on the inputs of the first layer. When t_{n+1} value is predicted, the inputs are shifted, and the value t_{n+1} is given as the input to the last neuron

of the first layer. A network may be supervisory trained, using the comparison between values predicted and received as an error measure.

A multi-agent predicting system is a population of intelligent agents performing independent analysis of incoming data and generating predictions [4, 3]. In this case subsequent elements of the input sequence(s) are supplied to the environment, where they become available for all agents (see fig. 2b). Each agent may propose its own predictions of (a subset of) the next-to-come elements of input obtained from the possessed neural network. Of course the network is trained by the agent using incoming data. On the basis of predictions of all agents, prediction of the whole system may be generated e.g. by the means of PREMONN algorithm [2]. In such a system introduction of evolutionary processes allows for searching for a neural network architecture and learning parameters most suitable for the current problem and system configuration, just like in evolutionary multi-agent systems.

4 Immune-Based Selection in Evolutionary Multi-agent Systems

The idea of *EMAS* was already described and successfully applied to several difficult problems including function optimization and prediction [3, 2].

The key idea of *EMAS* is the incorporation of evolutionary processes into a multi-agent system at a population level. This means that besides interaction mechanisms typical for agent-based systems (such as communication) agents are able to *reproduce* (generate new agents) and may *die* (be eliminated from the system). Inheritance is to be accomplished by an appropriate definition of reproduction, which is similar to classical evolutionary algorithms. A set of parameters describing basic behaviour of an agent is encoded in its genotype, and is inherited from its parent(s) – with the use of mutation and recombination. The proposed principle of selection corresponds to its natural prototype and is based on the existence of non-renewable resource called *life energy*. Energy is gained and lost when agents execute actions. Increase in energy is a reward for "good" behaviour of an agent, decrease – a penalty for "bad" behaviour (which behaviour is considered "good" or "bad" depends on the particular problem to be solved). At the same time the level of energy determines actions an agent is able to execute. In particular, low energy level should increase possibility of death and high energy level should increase possibility of reproduction [7].

In the simplest case the evaluation of an agent (its phenotype) is based on the idea of agent rendezvous. Assuming some neighbourhood structure in the environment, agents evaluate their neighbours, and exchange energy. Worse agents (considering their fitness) are forced to give a fixed amount of their energy to their better neighbours. This flow of energy causes that in successive generations, survived agents should represent better approximations of the solution.

In order to speed up the process of selection, based on the assumption that "bad" phenotypes come from the "bad" genotypes, a new group of agents (acting

as lymphocyte T-cells) may be introduced. They are responsible for recognizing and removing agents with genotypes similar to the genotype pattern possessed by these lymphocytes. Of course there must exist some predefined affinity function, e.g. using real-value genotype encoding, it may be based on the percentage difference between corresponding genes. These agents-lymphocytes may be created in the system in two ways:

1. vaccination – during system initialisation lymphocytes are created with random genotype patterns, or with the patterns generated by some other technique designed to solve a similar problem,
2. causality – after the action of death, the late agent genotype is transformed into lymphocyte patterns by means of mutation operator, and the newly created group of lymphocytes is introduced into the system.

In both cases, the new lymphocytes must undergo the process of negative selection. In a specific period of time, the affinity of the immature lymphocytes patterns to the "good" agents (possessing relative high amount of energy) is tested. If it is high (lymphocytes recognize "good" agents as "non-self") they are removed from the system. If the affinity is low – probably they will be able to recognize "non-self" individuals ("bad" agents) leaving agents with high energy intact.

5 Immunological Multi-agent System for Neural Network Optimization

The immunologically-enhanced selection is driven by two types of agents (computational agents and lymphocytes) and in case of neural network optimization may be described as follows.

First, the population of computational agents is initialized with random problem solutions (neural networks and learning parameters) and the initial energy level. Every agent is able to perform predictions of subsequent time-series values, after it acquires its actual value and modifies the weights of its neural network in one step of the learning process. During the described earlier *agent rendezvous* action it compares its fitness with neighbours and exchanges a portion of energy with them. When the level of energy reaches certain level, an agent looks for the neighbour that is able to reproduce, and they create a new agent, and then a fixed portion of the parents' energy is passed to their child. An agent dies when its energy falls below certain level – it is removed from the system and a lymphocyte is created based on its genotype.

The specific task for a lymphocyte agent is affinity testing – existing lymphocytes search the population for agents similar to the genotype pattern contained in a lymphocyte. If the lymphocyte survived the process of negative selection – it causes the removal of similar agent. Otherwise lymphocyte is removed from the system. In the proposed approach, the affinity is determined using the relation of the corresponding genes in the following way. Let $p = [p_1 \dots p_n]$ be a

Fig. 3. Prediction error obtained for EMAS (a) and iEMAS (b)

paratope (genotype pattern owned by the lymphocyte) and $e = [e_1 \dots e_n]$ be an epitope (genotype owned by the antigen – in the described system it is simply the genotype of the tested agent), and n is the length of the genotype. If d_{max} is the maximum deviation and c_{min} is the minimum count of corresponding genes, the construction of the set of corresponding genes may be considered:

$$G = \{p_i : \left| \frac{p_i}{e_i} \right| \leq d_{max}\}$$

The lymphocyte is considered as stimulated (its affinity reached minimal level) when $\bar{G} \geq c_{min}$, and considered as non-stimulated otherwise.

6 Preliminary Experimental Studies

The system was designed and implemented using distributed evolutionary multi-agent platform Ant.NET developed at AGH-UST (<http://antnet.sourceforge.net>).

The experiments were performed in order to show whether the introduction of the immunological-based selection mechanism into EMAS will make the classical energetic selection more effective. A distorted sinus function was used as a benchmark for prediction.

Evolutionary multi-agent system consisted of one evolutionary island, with initial population of 100 agents. The genotype of the agent contained the description of a feed-forward neural network (multi-layered perceptron) – count of neurons in hidden and input layers, learning coefficients. The networks were taught by the means of backpropagation algorithm with momentum. Before maturing, every lymphocyte undergone the negative selection process. During 100 system steps, if immature lymphocyte was stimulated by an agent with energy of 150 or higher, the cell was removed from the system.

In figure 3 the prediction error is presented in terms of fitness of the best solution in consecutive steps of the system activity. Each plot shows an average (and the value of standard deviation) of the prediction error obtained from

the 10 runs of optimization with the same parameters. Comparing the plots, it seems that introduction of the immunological selection allows for a bit quicker obtaining of the desired prediction accuracy (prediction error close to zero). Yet this result is not convincing and must be verified by further experiments.

7 Conclusion

In the paper an agent-based approach to optimization of the architecture of a predicting neural network was considered. An immune-inspired selection mechanism was proposed as an alternative to energetic selection used in evolutionary multi-agent systems. As the preliminary experimental results show, it allows for improper individuals to be removed from the system faster than using classical energetic selection, and thus allows for obtaining slightly better solutions in comparable time.

The approach seems to be especially adequate for solving problems in which fitness evaluation takes relatively long time, just like in the considered case of neural network architecture optimization, which requires training of the neural network each time it is evaluated [3]. By means of negative selection mechanism, agents that probably will not be able to construct an efficient neural network, may be removed before they complete the process of training.

Of course up till now it is too early to compare the method with various other optimization heuristics known from the literature. The work in progress should allow for such a comparison.

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