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Artificial immune classifier with swarm learning

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ABSTRACT

Artificial immune systems are computational systems inspired by the principles and processes of the natural immune system. The various applications of artificial immune systems have been used for pattern recognition and classification problems; however, these artificial immune systems have three major problems, which are growing of the memory cell population, eliminating of the useful memory cells in next the steps, and randomly using cloning and mutation operators. In this study, a new artificial immune classifier with swarm learning is proposed to solve these three problems. The proposed algorithm uses the swarm learning to evolve the antibody population. In each step, the antibodies that belong to the same class move to the same way according to their affinities. The size of the memory cell population does not grow during the training stage of the algorithm. Therefore, the method is faster than other artificial immune classifiers. The classifier was tested on two case studies. In the first case study, the algorithm was used to diagnose the faults of induction motors. In the second case study, five benchmark data sets were used to evaluate the performance of the algorithm. The results of second case studies show that the proposed method gives better results than two well-known artificial immune systems for real word data sets. The results were compared to other classification techniques, and the method is competitive to other classifiers.

1. Introduction

In the 1990's the artificial immune systems (AIS) became one of the important research areas of computational intelligent algorithms. AIS are based on the principles and processes of the natural immune system and applied to a wide spectrum of applications. The basics of AIS algorithms come from theoretical immune system, observed immune functions, models, and principles (Dasgupta, 2006). These algorithms have strong and robust information processing capabilities for solving complex science and engineering problems. AIS have a structure similar to that of the artificial neural network and just like it AIS have learning, adaptability, novelty detection, and optimization characteristics. The application domains of AIS are various fields of artificial intelligence, such as optimization (de Castro and Von Zuben, 2002; Campelo et al., 2005), anomaly detection (Gonzalez and Dasgupta, 2003; Forrest et al., 1994), data clustering (de Castro and Von Zuben, 2001), classification (Igawa and Ohashi, 2009; Leung et al., 2007; Watkins, 2001), fault diagnosis (Aydin et al., 2008; Branco et al., 2003), and security of information systems (Kim and Bentley, 2002). Although AIS development is in the early stage, they have been already applied to many practical applications.

Among the various characteristics of the natural immune system, there are three models proposed in AIS. These models are clonal selection, negative selection, and immune network models (de Castro and Timmis, 2002). In a negative selection algorithm, the purpose is to detect any abnormal condition of a system using a self data set. The clonal selection algorithm is an optimization and pattern recognition tool of the AIS (de Castro and Von Zuben, 2002). This algorithm is a population-based stochastic method, which is capable of optimizing multimodal functions and maintaining local solutions. In this method, the proliferation and affinity maturation process are used to evolve the population. The immune network model was first proposed by Jerne (1974). In this model, the immune system constitutes a network of cells and molecules. These molecules and cells maintain interactions between not only an antibody and an antigen but also the antibodies themselves. The similarity among antibodies causes a negative response in the immune network system, so similar antibodies will be eliminated from the network.

Different immune models have been developed for pattern recognition and especially classification problems. The basic study, which can be regarded as a supervised classifier method, was proposed by Watkins (2001). His classifier system was named

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the Artificial Immune Recognition System (AIRS), and it is based on artificial recognition balls. This classifier method gives very effective results when it is compared to the other classifier methods. However, this method has some drawbacks. First, each training antigen is given to the classifier only once. This method may not guarantee the best memory cell (B-cell) for the presented antigen. Some antibodies are generated randomly, and they are the mutated version of the existing antibodies. The stimulation level of an antibody is inversely proportional to the distance of this antibody to an antigen. In each step, one B-cell is optimized, and this does not guarantee an optimal classifier. The least stimulated B-cells are removed from the population. Because only one antigen is evaluated in each step, the least stimulated B-cell for an antigen has a very high affinity for the other antigens. This causes a negative effect on the immune classifier as a whole.

Another study proposed by Leung et al. (2007) uses the immune system for classification. Their study uses one B-cell instead of a B-cell pool and an exemplar for each class. Each exemplar consists of a few instances per class. But their study does not use affinity-based mutation and cloning. The mutation and cloning processes are applied to each B-cell in random, therefore requiring the generation of many clones in each step. The algorithm, which is very slow, reaches its maximum performance after an average of 237 iterations. Igawa and Ohashi (2009) proposed a negative selection based classifier method. Their method uses negative and clonal selection algorithms and gives efficient results for some benchmark data sets. However, the method must be re-operated to generate memory cells of each class. Furthermore, an alpha control parameter must be readjusted for different data sets. Another problem is that only one memory cell is generated in each step. Zhong et al. (2006) proposed an artificial immune system as an unsupervised classifier for remote sensing imagery problems. The fundamental mechanism of the unsupervised classifier is based on antibody population evolution, clonal selection, and memory cells development. In the unsupervised classifier, the antibody population is updated for each antigen, and the best antibodies are taken as memory cells; however, the antibody population for only one antigen might have a negative effect on the immune system.

In this study, an artificial immune classifier with swarm learning (AICSL) method is proposed. The proposed method uses clonal selection and particle swarm optimization for evolution of the memory cell population. The evolution of an antibody in the search space depends on the antibody's affinity and the affinity of its neighbors. With these artificial immune classifiers, the new candidate memory cells are randomly generated by a mutation operator. Then, the worst memory cells are replaced with the best antibodies. A different mutation operator is used to evolve the B-cell population in AICSL. Each antibody belongs to a determined class, and it moves towards this class. The affinity of each antibody is determined according to three criteria: its affinity, its neighbors, and its best affinity found so far. There is no population control mechanism in this system, as the population consists of a predefined number of B-cells. The optimization is performed globally and the best affinity and position are not lost in the evolution process. The proposed method is applied to two case studies. In the first case study, the faults of the induction motors are classified. The performance of the proposed method is compared to the other classifiers in the second case study on five benchmark data sets.

The remainder of the paper is organized as follows. Section 2 provides a brief description of natural and artificial immune system. Section 3 explains the particle swarm optimization. Section 4 describes the proposed algorithm. In Section 5, the results of case studies are provided. Finally, the conclusions are provided in Section 6.

2. Natural and artificial immune systems

Our natural immune system protects our body from foreign cells called antigens by recognizing and eliminating them. This process is called an immune response (Perelson, 1989). Our immune system constitutes a self-defense mechanism of the body by means of innate and adaptive immune responses. An adaptive immune response contains metaphors like pattern recognition, memory, and novelty detection. The fundamental components of the immune systems are lymphocytes or white blood cells, which are divided into two classes: B- and T-cells. B-cells have a more important function than T-cells because each B-cell has its distinct chemical structure and secretes many antibodies from its surface to eliminate the antigens. A huge variety of antibodies are generated to neutralize and eliminate antigens. Each antibody is constituted by a specific B-cell whose aim is to recognize and bind to antigens (Jerne, 1974). In the immune system, an important function is clonal selection. Clonal selection determines how an immune response is given when an antigen is detected by a B-cell. Fig. 1 shows the cloning process of a B-cell receptor when it recognizes any antigen with a certain affinity.

In Fig. 1, once a B-cell is stimulated through a certain affinity to any antigen, it immediately produces its clones and it exposes to a hypermutation process. This process produces new cells to match the antigen more closely. The B-cells that do not match any antigen will eventually die. Activated B-cells produced by the clonal selection process are selected to become memory cells. The main characteristics of the immune system are learning and memory (de Castro and Von Zuben, 2002). The adaptive immune system can learn the structure of an antigen and remember this antigen for future response. This factor ensures the reinforcement learning in the natural immune system. Immune network theory is different from clonal selection with a distinctive principle. While clonal selection only controls the interactions between antigens, the immune network controls this process both between

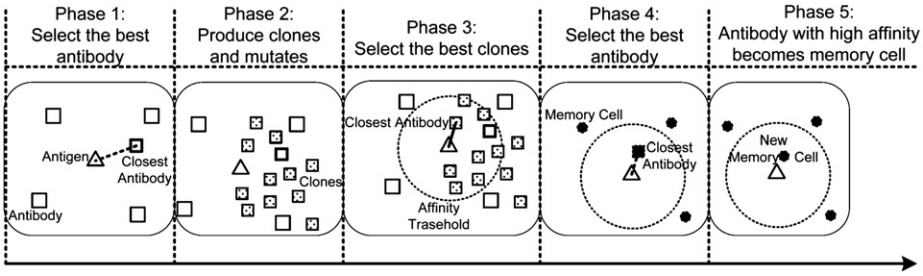

Fig. 1. The process of clonal selection.