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ADAPTIVE MECHANISMS OF THE NEUROEVOLUTION METHOD FOR NEURAL NETWORK SYNTHESIS

Artificial neural networks (ANN) are one of the directions in the development of artificial intelligence systems. The main idea is to simulate as close as possible the work of the human nervous system. Namely, ability to learn and correct errors. An ANN simulates not only the activity, but also the structure of the human nervous system. It consists of a large number of separate computing nodes (neurons) that are coupled by connections (synapses). Connections differ in

relative weight (importance), and neurons are grouped into layers. Input data is processed sequentially at all network layers.

All the tasks that ANN can solve are related to learning (usually this process called training) in one way or another. The main applications of neural networks include forecasting, decision making, pattern recognition, optimization, and data analysis. Creating an ANN consists of two main stages:

1. choosing the ANN structure (architecture or topology);
2. setting the weights of all neurons and connections of the ANN (training).

To perform the ANN training stage, the most common method is the Back propagation method (BP), which allows adjusting the weights in multi-layer complex ANN using training data sets. However, despite its popularity, the BP has a number of disadvantages:

1. indefinitely long learning process;
2. the problem of overfitting the network;
3. excessive dependence on the expert.

ANNs have always been attractive from an intuitive point of view. In this regard, there was an assumption that it may be appropriate to use another borrowing from nature: evolutionary strategies and, in particular, neuroevolution methods. Neuroevolution methods have become popular due to their comprehensiveness and a wide range of tasks to solve. These methods help you make a complete network synthesis: search for the most appropriate topology and configure its parameters. However, one of the main problems of applying such methods is their convergence in the area of local extremes, instead of the global optimum for the task. This problem is often caused by insufficient population size or insufficient diversity of individuals within the population. The solution to this problem can be the introduction and adjustment of adaptive mechanisms at different stages of neuroevolution methods.

Thus, in a number of studies, it has been noted that mutation probability increase helps to prevent premature convergence of methods. However, it is worth noting that a significant structural diversity of individuals can be achieved at the mutation stage. To do this, it is necessary to introduce an additional mechanism for evaluating individuals based on different criteria that will help assess the connectivity of the network, correspondence of the structural complexity to the task to be solved and entanglement of the network. Based on the values obtained, a specific type of mutation can be selected in each specific situation:

1. removing or adding a hidden neuron;
2. removing or adding connections between neurons;
3. removing or adding feedback loops (for recurrent ANN);
4. changing the weight of the connection (or feedback loops);
5. removing or adding a hidden layer (for deep ANN);
6. changing the type of activation function inside the neuron.

The uniform crossover (UC) is one of the most effective recombination operators in a standard genetic algorithm. Setting up the probability of passing a parent's gene to a descendant in a UC can significantly increase its effectiveness. Also, using the UC operator allows to apply the so-called multi-parent recombination, when more than two parents are used to generate new individual. However, the introduction of a selective pressure mechanism before using UC will allow us to accurately assess the dominant characteristics of the best individuals in the population. This mechanism is based on a combination of rank selection and criteria that allow evaluating excessive memory consumption and networking approximation characteristics. In this case, the parent pool for crossover will be filled only with the best individuals, and the probability of inheriting genetic information from each of the parents will be proportional to their effectiveness.

Thus, the using of such modifications of classical neuroevolution methods allows maintaining adaptability by:

1. maintaining the structural (topological) diversity of individuals within the population;
2. control of excessive growth of "weak" individuals within populations.

This allows to get the most optimized ANN for a specific task. Moreover, such mechanisms significantly increase the efficiency of neuroevolution methods when working on modern parallel computing systems, helping to reduce the share of overhead costs for transferring information between computing threads and using RAM.