NEURAL NETWORKS DEFINITION ALGORITHM

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At present, there is not a general methodology for neural network definition. In this work we propose an algorithm highly inspired on biological concepts for generating neural networks oriented to solve particular problems given on terms of input and output. With this algorithm we pretend to specify formal tools of general use for network definition, and to disclose underlying processing structures of the living organisms.

1. INTRODUCTION AND APPROACHES

The main problem in designing artificial neural networks is that there are not standard tools to develop networks oriented to solve specific problems; in other words, the designer has not a methodology to work with.

The biological neural networks are a good example of solving a particular problem: the survival. Given that living organisms are forerunners in networks definition, and that most significant advances on neural networks theory came from biological influence (physiology, anatomy, etc.), we think that this field will still inspire new models and paradigms.

The method used to obtain this biological networks is the natural selection, which has implicit some mechanisms as network coding and decoding, mutation and cross-over of these codes, and performance evaluation of these networks in the environment they will work. This subject has been well raised from the genetic algorithms[1] that define the necessary operators to implement a search method starting with a genetic code, a decoder algorithm and a fitness function.

This selective process implies that the best neural networks we obtain are given by accumulating little bit changes, that will accepted or suppressed depending on whether they favour or damage, respectively, their capacity for a specific task.

The genetic code is the necessary information to obtain a neural network with a decoder algorithm. Each feature of the network is expressed in the genes, that are meaning units into the code.

The concepts of genetic code, embryogenesys and evolution are the main keys in the development of the algorithm we propose.

2. ALGORITHM CONSIDERATIONS

As we pretend to do a model of the strategy that living organisms follow in searching solutions, we have divided the process into the following blocks:

1. Specifications of the problem:
   - Input set
   - Output set
   - Input/Output relations
   - Performance required

2. Random generation of the genetic codes

3. Development of each code to obtain the neural networks

4. Gross adjustment of the network in the phase of synaptic plasticity

5. Weights adjustment in a non-supervised way

6. Fitness evaluation of each network with the controlled sample

7. Stop if we got a network with the required performance

8. To obtain the next codes from the best networks we have got

9. Go to 3

This algorithm implements a genetic search method that constitutes the natural selection process that we need; steps 3 to 5 carry out the main biological processes to generate coherent networks.

The main characteristics of these processes are:
A) Embryologic Development

Living organisms carry out an embryologic period in which they form an organism starting from a single cell containing the genetic code that specifies the way to follow. The main processes implicated in this period are cellular bipartition and a gradual specialization of the obtained cells. When this phase is finished we get a feasible solution to the problem we want to solve.

A blast, cell capable to be divided through bipartition generates two new cells. These could be final cells that will specialize in their own function, or new blasts that will generate more cells in the same way.

In our model we work with 3 kinds of cells:
1. **Input cells** which have connections with the input of the system
2. **Output cells** that give an output to the system
3. **Neurons** that process information

The number of input and output cells will be specified by the user depending on the problem, and the number of neurons obtained would mean the processing capacity of the neural network.

B) Synaptic Plasticity

In general, the neuroblasts are too much enthusiast making neurons and connections, so that we call feasible solution the network obtained in the embryologic process because it perform a generic processing and need to be adapted to the particular conditions of the environment in which the network will work. This phase is called synaptic plasticity period and in it the network presents a high flexibility to raise connections in the zones in which they are necessary and to eliminate the misused connections, even to cause cell death to the useless cells[2,3].

C) Learning

The learning process is a more precise synaptic plasticity method. In general, it doesn’t imply the raise of new branches since it only makes the connections to become stronger or weaker. These processes are included in the neuronal physiology, so they are intrinsic to the neuron, and are driven by the information going through the connections. In our model, learning is given by the Hebbian rule, that works in a non-supervised way.

These three processes are necessary for the final development of the network, but they have a decreasing order of importance, so that we might not get a good network just adjusting a bad solution.

D) Simulating

The step 6 refers to the fitness evaluation. This is made translating the resulting data structure into the subroutines of a neuronal networks simulator. Presently we are using the Rochester Connectionist Simulator[4] because of its flexibility and the capacity to implement complex learning rules and propagation delay.

As the input-output relations are introduced, the algorithm simply compares the output of the network with the output pattern wanted to evaluate the network performance, and this value will be the fitness for this network. This relations may be simple (pairs of input-output patterns) in the case of classifiers, or complex to implement classical conditioning. In this case the learning rule is a version of the Hebbian rule.

To obtain the output, the network must become stable, refusing those networks that can’t reach a steady state.

3. NETWORK DEVELOPMENT

In defining the network development model we had into account important hypothesis about the generation, migration and connection of the neurons processes implicated in the embryologic period of biological neural networks:

1. The final position and connection patterns of the neurons are determined by genetic factors (the information in their genetic codes) and epigenetic processes.

2. The neuronal connections are not made in a random way, but they are determined by factors appeared in the neurulation and migration phases (skeletons of special cells and chemical substances).

They two are strongly supported by experimental evidences[2,5]. With respect to the first hypothesis, it has been proved that the embryologic process is driven mostly by the genes at the cell level, giving less importance to external factors[6].
The second hypothesis is more important because it is the key for the model of network connectivity we have implemented. Basically, the axons advances expanding a growth cone driven by chemical (mostly), mechanical and electric factors[2]. In this sense, the chemical affinity hypothesis stands by the idea that axons follow chemical ways across the network to make connection with one or a group of target cells. In other way the guidance of pioneer axons is explained by specific stepping-stone cells. These mechanisms are very exact and decide the final development of the network.

Based in these two hypothesis, our model stands by the building of an underlying structure during the embryologic period that will determine the connections of the cells. The final number of cells and the patterns of connection will be genetically predicted.

To implement this mechanism we are using fractal methods[7,8] because they give very good results in simulating natural processes. Moreover, the genetic control of the development refers directly to a subset of these methods: the deterministic fractals. They are generated by a grammar, enunciated in our case in the following terms:

Terminal symbols = { connection, neuron, input, output }  
Non terminal symbols = { BLAST }  
Rules = {  
  1) BLAST -> BLAST connection BLAST 
  2) BLAST -> neuron 
  3) BLAST -> input 
  4) BLAST -> output }  
Initial symbol = BLAST

The meaning of this grammar is that the process starts with a single BLAST. Then, applying recursively one of the rules at a time we will have a number of neurons, inputs, outputs and links that constitute the final network. An example of this process is as follows:

```
BLAST
  1
  
BLAST connection BLAST
  3  1
  
input BLAST connection BLAST
  2  4
  
neuron output
```

The networks obtained with this method have the properties of the fractal objects:

- they generate complexity from simplicity
- the final result is sensitive dependent on the initial conditions
- they can generate a high number of different networks introducing small changes in the rules
- self-similarity and self-affinity: the underlying neuronal structures generated are repeated at different scales in the network

We can see all these characteristics in the living organisms and particularly in the complex neuronal circuits; because of that fractal methods are very useful to study chaotic processes in general and cerebral chaos in particular[9].

In fact, the grammar showed is too simple to obtain our net; so we have added some specific features to the symbols (terminal and non terminal) as the kind of connection and internal variables of the cells. In this way, we have defined a high level grammar that expresses the data structure of the algorithm, and can obtain more complex productions than those generated by a linear grammar.

In a graphic sense, we could say that each blast division leaves a way in form of connections that will be followed by the axons to make the synapsis of the network[10]. The resulting structure will be the connection tree.

With this structure we can obtain a very high diversity of networks, establishing a unanimous correspondence between the connection tree and the network. Yet, as the blasts are divided following a finite set of rules (expressed in the genetic code) this imposes restrictions to the possible nets that will be generated, so that, for a given set of genes a family of networks will be obtained with a higher or lower capacity to solve the given problem.

4. SUMMARY AND FUTURE DIRECTIONS

The most interesting features and objectives of the work we present are:

1. The definition of an algorithm to obtain automatically a neural network to solve a particular problem from the
input-output characteristics.

2. The networks developed with this algorithm are oriented to massive processing of information.

3. The artificial neuronal networks obtained are similar to biological ones, using the main paradigms the living organisms use.

4. The disclose of underlying processing structures present in the biological models.

5. The specification of formal tools to develop a methodology of neural networks definition.

At present, we are making a study of some outstanding features of the generated networks, principally oriented to the following aspects:

- the most commonly used structures and their implications
- the influence of the convergence and divergence degree at different stages of the embryologic period
- raising of processing neural groups and their structure
- the mathematical meaning of self-similarity and self-affinity in processing information

The package to implement the genetic algorithm has been developed on a SUN-4 WorkStation, and now we are refining the modules to obtain better searching times and the total convergence of the method.

Presently we are modifying the method to obtain three-dimensional networks including spatial coordinates to the blast; this new characteristic has two objectives: to give a measure of the distance between neurons that will be used as a propagation delay of the neural impulse, and supply the information to obtain some kind of networks representations.

REFERENCES


