Model of biological ANN based on homeostatic neurons

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Abstract: This paper presents an artificial neural network that is composed of homeostatic neurons. The homeostatic neuron is based on McCulloch-Pitts model of artificial neuron with some modifications. The basic requirements for this model is the simplicity and similarity to biological neuron. It is supposed that the neuron is able to maintain its parameters in a way that maximizes its chances to survive. The probability of survival in the neural network depends on how well is accepted the output by other neurons. The homeostatic neurons form a neural network, that is aimed to model biological neural network. The purpose of this network is not to perform any specific task (such as prediction) but to simulate precesses in human brain, e. g. the loss of attention.

Key-Words: - homeostasis, artificial neural network, biological neural network, learning, stability,

1 Introduction

The most commonly used prototype of artificial neural networks (ANN) is the McCulloch-Pitts neuron. This neuron is inspired by the biological neuron, however, there are many differences. The biological neuron is an extremely complex structure, that can not be exactly simulated. The McCulloch-Pitts model is a strong simplification of this structure. In this research, we tried to design a new model that takes advantage of the simplicity of the McCulloch-Pitts model and is adapted in some aspects to biological neurons. One of the basic characteristics of any biological system, including the neural cell, is the ability of homeostasis. Homeostasis is a property of system that regulates its internal environment and tends to maintain stable conditions. There are several forms of homeostasis, such as maintainance of the salinity or temperature. In this paper we propose information homeostasis, i.e. maintaining such a state of every neuron where its utility for other neurons is maximal. The neurons with weak feedback from the environment (from other neurons) will be pruned. This idea has its biological foundations, as it has been proven that there is a strong pruning in the human brain during the early life. According to [1], up to 41 % of the neurons die. This research is aimed to adapt the principle of homeostasis to ANN. Both homeostasis and ANN have been already subject of many studies, however, there are only a few papers that discuss these topics together. In [2] the role of homeostasis for immune system is discussed. The hardware realization of neural networks also makes possible the use of homeostasis [3]. This paper focuses on models of cortical neural cells, as suggested in [4]. Also, several models of more complex neural structures have been made. In [5], a network for generating signals that are used in human body is described. The model of homeostatic neuron can be useful in connection with another principles [6,7]. The electric signal is in the scope of the majority of the model, such as [8].

This paper is structured as follows: section 2 presents the theoretical concepts of the learning, section 3 describes the practical realization and the results and section 5 concludes the paper.

2 Methodology

2.1 Theoretical concept of homeostatical artificial neuron

The first step was the definition of the basic unit, the artificial neuron. The proposed neuron in based on McCulloch-Pitts model. The forward phase is identical to this model, i.e. the neuron sums up the inputs and executes the activation function:

\[ f(x) = f(\sum_{i=0}^{n-1} x_i w_i) \]  

In this research, we always used the sigmoid function as the transfer function:

\[ f(x) = \frac{1}{1+e^{-ax}} \]  

The homeostatic artificial neuron has two types of inputs and one output.
The first type of input is the signal that comes into its dendrites. This input is independent—it comes from the external world (from the point of view of the neuron, in fact it's the output of another neuron) and doesn't depend on the setting of the neuron (the neuron can only change its, which doesn't change the input itself but the part of the input that comes into the neuron).

The second input are the weights of another neurons that accept the output from the reference neuron. These weight (the weights of other neurons) are used to calculate the utility. In order to make the notation more clear, the term input weight $w_i$ is used to denote the weights of the reference neuron and the term output weight $w_o$ denotes the weights of other neurons that are accepting the output of the reference neuron. The output weights are used for the calculation of the overall utility. The output of the neuron is a signal from $(0;1)$ interval that is calculated according to (1) and (2) as in standard McCulloch-Pitts neuron.

It is supposed that the neuron ‘wants’ to be useful for other neurons (and therefore for the network), so that it tries to increase the output weights. To do so, we assume that the neuron has the information about the output weights. This is possible in biology because, as we can imagine, the neuron knows which part of its output energy is accepted by other neurons. There are several ways how to calculate the utility.

### 2.2 Searching the homeostatical position of the neuron in the state space

The simplest way how to calculate the utility is to sum up the output weights

$$ u = \sum_{i=0}^{n-1} |w_i^o| $$

The advantage of this manner is that it can be easily realized by biological cell. The neuron knows what is the sum of the output weight because it depends on the output energy that is absorber by other neurons. In other words, the neuron sends the output signal and observes which part is accepted by other neurons. The neuron wants to maximize the rate of absorbed energy to total energy. If the neuron has low utility, it commits a ‘suicide’ and it leaves its resources to another neurons. There are several ways how to calculate the utility.

### 2.3 Homeostatic ANN

This idea can be proven by organizing the homeostatic neurons into a ANN. The learning process of each unit is divided into these steps:

1. set the weights (can be done randomly)
2. compute the forward phase according to (2) and (3)
3. compare the desired output and the real output
4. update the weights of the output neuron
5. change one weight of the first neuron
6. compute the forward phase with the new weights
7. update weights of the output neuron
8. if the weight from the first neuron in the hidden layer to the output neuron was improved, then confirm the change, otherwise make the change in other direction
9. repeat steps 6 to 8 with all the weights
10. repeat steps 2 to 9 with all the neurons (except for the output neuron)

This process is repeated for all the neurons until the required function is achieved. In the multi-layer homeostatic network, the principal problem is the delay of the signal. The information about the utility reaches the neuron in different time than the input. The solution of is probably the dynamics of the network which can be set to sufficiently low level so that the utility will reach the neuron in time when the input is equal or almost equal to the previous input. Also, the neuron can be equipped with a memory, from which can be called the information about the utility in some previous step.

3 Results

The above described neuron was tested as a part of a neural network. The topology of this network was [6,6,1]. 3 input samples composed of binary number {0; 1} were used. The desired output was out of {0;1} set. Differently from usual ANN tests, the main purpose of this test was not to measure the convergence (which will be obviously slower than in case of another algorithm, such as back-propagation), but simply to prove the stability and the ability of learning. In this test, there were improved only the weights, but as we can imagine, similar algorithm can be used also for the setting of the slopes and the thresholds. From the algorithm we can see the basic disadvantage of this method (in comparison to backpropagation): the necessity of the computation of the forward phase in each step of the learning process. This will tend to an increase of the computational time in large network. Solution of this problem is probably the partial or full parallelization of the upgrade algorithm. The brain is also strongly parallel structure, therefore the parallelization seems to be the correct solution. If the utility of a neuron is lower than some threshold in 10 following steps, the neuron sets all of its weights to 0, it “commits suicide”. In the test, there were used both calculation of the utility according to (3) and (5). The calculation according to (5) was significantly faster. In the future test, we will add terms to eq (5) or (6), which means that the utility converges to (3), that is theoretically the correct method.

4 Conclusion

The tests have proven the viability of the idea of the homeostatic neuron. Although there is still a lot of work left, we can already conclude that the homeostatic artificial neural network is able to set its weights independently, without need of any teacher. The neurons are not trying to fulfill any given function, but only to increase their importance to other neurons (with the exception of the neurons in the output layer that need the information about the correctness of the function of the whole network). The speed of learning is significantly slower than when another algorithms (e.g. back propagation) is used, but the learning process is quite stable. The tests proved the functionality of this network, on the other hand it was also proved that many improvements must be done in order to make this network faster. In the following research, we will concentrate on the calculation of the utility and the learning process. The proposed network has another advantages, from which the most important is the similarity to biological neuron. This quality may be used in several applications, for example, the simulation of biological neural networks. We are particularly interested in modelling the brain function. In the future research, this network will be improved and adapted to work with useful data.

References: