proceedings

Proceedings

Use of Multiple Astrocytic Configurations within an Artificial Neuro-Astrocytic Network †

Francisco Cedron *, Sara Alvarez-Gonzalez, Alejandro Pazos and Ana B. Porto-Pazos

Computer Science Department, Research Center on Information and Communication Technologies, University of A Coruña, 15071 A Coruña, Spain

* Correspondence: francisco.cedron@udc.es; Tel.: +34-881-01-2666

† Presented at the 2nd XoveTIC Conference, A Coruña, Spain, 5–6 September 2019.

Published: 7 August 2019

Abstract: The artificial neural networks used in a multitude of fields are achieving good results. However, these systems are inspired in the vision of classical neuroscience where neurons are the only elements that process information in the brain. Advances in neuroscience have shown that there is a type of glial cell called astrocytes that collaborate with neurons to process information. In this work, a connectionist system formed by neurons and artificial astrocytes is presented. The astrocytes can have different configurations to achieve a biologically more realistic behaviour. This work indicates that the use of different artificial astrocytes behaviours is beneficial.

Keywords: astrocyte; artificial neuron-astrocyte network; genetic algorithm; cooperative co-evolutionary genetic algorithm

1. Introduction

It has recently been shown that information processing in the brain is not carried out solely by neurons [1]. Astrocytes from glial system work together with the neurons, using a bidirectional communication called tripartite synapses [1].

From the perspective of artificial intelligence, this finding represents a new approach to connectionist systems (CS) [2]. Most of the CS that are used in tasks such as speech recognition prediction or medical diagnosis, only contain neurons [3]. The implementation of a CS with bidirectional communication between neurons and astrocytes supposes a more biologically realistic system (see Figure 1) that had improved the results obtained by artificial neural networks (ANN).

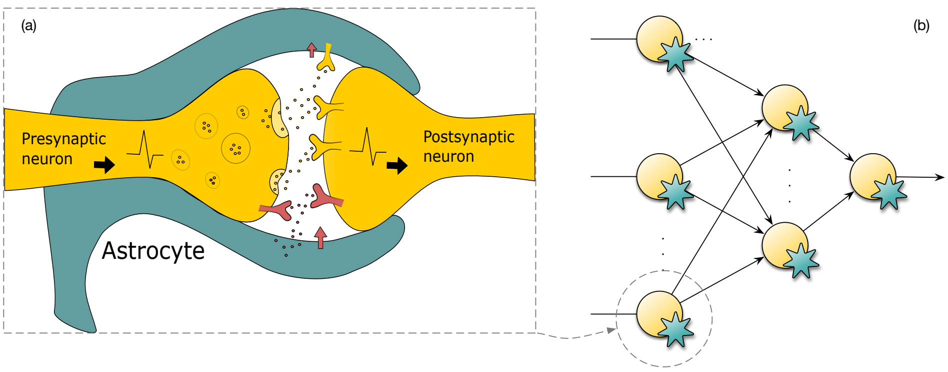

Figure 1. (**a**) Scheme of tripartite synapse in the brain. (**b**) ANAN structure, where artificial astrocytes and neurons are represented by green and yellow colors, respectively.

The simulation of astrocyte behaviour is based on biological observation. Unlike neurons that are electrically excitable and their communication is in milliseconds the astrocytes are slower, they communicate by means of calcium waves [4], taking seconds. To represent this behaviou, varios algorithms have been implemented that can be seen in [5,6] biological astrocytes can boost or depress the exchange of neurotransmitters in the synaptic space [4]. These properties are collected in artificial astrocytes as hyperparameters [5]. The behaviour of the astrocytes on a different time scale than that of the neurons means that learning techniques based on the gradient cannot be used in the network because the elements of the network have non-smooth and discontinuous functions. This property is not a limitation because techniques such as genetic algorithms (GA) can be used for training because have no restrictions on functions.

The proposed method has been tested using different network architectures with a classification problem extracted from the UCI machine learning repository [7]. The results obtained by the ANAN are superior to those obtained with a classic ANN.

2. Cooperative Co-Evolutionary Genetic Algorithm to Train Networks

ANANs include elements that are non-smooth and discontinuous so gradient based techniques cannot be used to perform the training phase.

For the learning phase it has been decided to use evolutionary learning techniques [8]. The use of canonical genetic algorithms has been ruled out because all the parameters of the ANAN (weights and parameters of the astrocytes) are too variable. It has been decided to use the cooperative co-evolutionary cooperative genetic algorithm (CCGA) because it allows the use of several species with different genotypes. The objective of the species is to work together to thrive.

The way to train ANAN with CCGA is by using two species: the weights of the net and the astrocytic parameters.

3. Proposal

This study aims to determine whether the use of different astrocytic behaviors improves the results obtained by the ANN and also those that can be obtained by an ANAN using a single astrocytic configuration across the entire network.

In order to train the ANAN with the two approaches, two different codings are used. For the approach using the same astrocytic configuration only the parameters of the astrocytes are stored once. The approach which using different astrocytic behaviours stores the astrocytic set-up for each layer.

4. Experiments and Results

The ANN and the ANAN have been compared under the same conditions. The only difference is that the ANN does not have astrocytes and a CCGA is not necessary since it only uses one species and a canonical GA is used instead.

The dataset used is breast cancer which analyzes the presence of cancer using 9 characteristics in 699 patients (9 inputs; a binary output) [9].

To secure independent results, 10cv cross validation was implemented [10]. Thus, 10 different sets were obtained where each of them include: 60% training patterns, 20% validations patterns and 20% test patterns. It was also used 10 different initial genetic populations. This means 100 runs to the cross validation set-up. Wilcoxon signed rand test was used to corroborate statistical significance [11].

As expected, ANAN obtains better results than ANN (see Table 1). ANAN with a different astrocytic configuration in each layer gets the best results when using networks with two and three hidden layers. This suggests that the use of astrocytes is more beneficial with larger networks and that different types of astrocytes are needed to complement each other.

Table 1. Comparative study of the classification accuracy (test values). The values described in the table refer to average performance (100 different runs) and the statistically significance (* $p < 0.05$, ** $p < 0.01$ and *** $p < 0.001$). The asteriscs compare ANAN to ANN. The architecture shows the number of neurons used on each hidden layer.

Architecture	ANN	ANAN	
		Single Astrocityc Configuration	Astrocytic Configuration for Each Layer
1 hidden layer (7)	90.34% ± 2.34%	90.75% ± 3.63%	90.43% ± 3.40%
2 hidden layers (7,3)	90.50% ± 2.25%	91.25% ± 3.88% **	91.37% ± 2.96% ***
3 hidden layers (12,8,3)	90.78% ± 2.21%	91.28% ± 4.96% **	92.12% ± 4.09% ***

Funding: This work has received financial support from the Xunta de Galicia and the European Union (European Social Fund—ESF).

Acknowledgments: This project was also supported by the General Directorate of Culture, Education and University Management of Xunta de Galicia (Ref. ED431G/01, ED431D 2017/16), the "Galician Network for Colorectal Cancer Research" (Ref. ED431D 2017/23), and the Spanish Ministry of Economy and Competitiveness via funding of the unique installation BIOCAI (UNLC08-1E-002, UNLC13-13-3503) and the European Regional Development Funds (FEDER). All the experiments were supported by the computing resources at the Supercomputation Center of Galicia(CESGA), Spain.

References

1. Araque, A.; Parpura, V.; Sanzgiri, R.P.; Haydon, P.G. Tripartite synapses: Glia, the unacknowledged partner. *Trends Neurosci.* **1999**, *22.5*, 208–215.
2. Porto-Pazos, A.B. Modelos Computacionales para Optimizar el Aprendizaje y el Procesamiento de la Información en Sistemas Adaptativos, Redes Neurogliales Artificiales (RR.NG.AA). Ph.D. Thesis, University of A Coruña, A Coruña, Spain, 2004.
3. Goodfellow, I.; Bengio, Y.; Courville, A. *Deep Learning*; MIT Press: Cambridge, MA, USA, 2016.
4. Perea, G.; Sur, M.; Araque, A. Neuron-glia networks: integral gear of brain function. *Front. Cell. Neurosci.* **2014**, *8*, 378.
5. Alvarellos, A.; Pazos, A.; Porto-Pazos, A.B. Computational models of neuron-astrocyte interactions lead to improved efficacy in the performance of neural networks. *Comput. Math. Methods Med.* **2012**, *2012*, 476324.
6. Cedron, F.; Alvarez-Gonzalez, S.; Pazos, A.; Porto-Pazos, A.B. Modelling Astrocytic Behaviours to improve connectionist systems. In Proceedings of the 18th National Meeting of the Spanish Society of Neuroscience, Santiago De Compostela, Spain, 4–6 September 2019.
7. Dua, D.; Graff, C. *UCI Machine Learning Repository*; University of California, School of Information and Computer Science: Irvine, CA, USA, 2019. Available online: http://archive.ics.uci.edu/ml (accessed on 16 July 2019).
8. Holland, J. Adaptation in natural and artificial systems: An introductory analysis with application to biology. In *Control, and Artificial Intelligence*; U Michigan Press: Oxford, UK, 1975; pp. 17–18.
9. Tan, M.; Eshelman, L.J. Using Weighted Networks to Represent Classification Knowledge in Noisy Domains. In Proceedings of the Fifth International Conference on Machine Learning, Ann Arbor, MI, USA, 12–14 June 1988; p. 121.
10. Cantu-Paz, E.; Kamath, C. An empirical comparison of combinations of evolutionary algorithms and neural networks for classification problems. *IEEE Trans. Syst. Man Cybern. Part B Cybern.* **2005**, *35*, 915–927.
11. Wilcoxon, F. Individual Comparisons by Ranking Methods. *Biom. Bull.* **1945**, *1*, 80–83.