Improving the performance of impulse neuro–glial network

Peter Gergeľ

Department of Applied Informatics, Comenius University in Bratislava
Mlynská dolina, 84248 Bratislava, Slovak Republic
Email: peter.gergel@gmail.com

Abstract

Research in neuroscience over the past few decades has shed new light on glial cells which were always considered as purely passive supportive cells. New data provides evidence that astrocytes, a group of glial cells, possess important physiological functions that distinguish them from passive cells. It is now known that astrocytes are actively involved in neuronal communication regulation and synaptic transmission. Similar to neurons, astrocytes are integrated into networks that enable them to communicate with one another over long distances using Ca^{2+} signals. Since this is a relatively new area of research in neuroscience, computational models (mainly connectionist) are still missing. In this paper we briefly introduce astrocytes, focus on existing connectionist models and present technique that yields more successful performance.

1 Introduction

According to current knowledge of neuroscience, two types of brain cells are distinguished: neural cells and glial cells. Population of neurons is characterized by the ability to generate action potential whereas glia were always considered as passive non-excitable cells. Neurophysiological findings at the turn of the 90s began to shift this perspective by providing evidence that glia cannot be longer considered as passive cells since they possess mechanisms for neural and synaptic regulation and modulation.

It is well-known notion that glia outnumber neurons by tenfold as taught by many neuroscience textbooks, but more recent evidence debunks this concept and claims glia-to-neuron ratio is in reality close to one (Hilgetag and Barbas, 2009). Four types of glial cells are distinguished: *oligodendrocytes*, *microglia*, *ependymal cells* and *astrocytes*. First three types are highly specialized and responsible for myelination, immunity and production of cerebrospinal fluid. Astrocytes account for most potent and functionally richest type that modulates neuronal activity on multiple levels. Besides their crucial role in neural development and production of neurotrophic factors, they are essential in regulation of extracellular level of pH and K^{+}, glutamate metabolism, nurturing neurons and maintaining blood–brain barrier.

Important milestones in history of glial research included discovery of negative resting membrane potential in astrocytes and membrane depolarization by neural activity (Orkand et al., 1966) and formation of glial syncytium (Brightman and Reese, 1969). In terms of current knowledge astrocytes are considered to be chemically excitable by specific neural molecules to which they respond with increased intracellular Ca^{2+} oscillations and release of *gliotransmitters* that regulate and modulate neuronal and synaptic activity.

Despite the fact that glial research is for the last decades very popular in neuroscience, in the area of computational modeling lack of interest still persists. In this paper we focus on existing connectionist models of multi–layer perceptron (MLP) with *artificial astrocytes* and present technique that yields more successful performance.

2 Previous work

In the area of computational neuroscience two modeling paradigms (abstractions) are considered: *biophysical* and *connectionist*. While first paradigm focuses on physicochemical properties of biological system using mathematical formalizations, second one makes abstraction over low-level mechanisms and tries to comprehend the system from higher level.

Despite plethora of biophysical models of astrocytes and their interactions with neurons, connectionst models are still missing. For an overview of biophysical models I suggest Oschmann et al. (2017), Volman et al. (2012), Wade et al. (2014).

Although not considered as a computational modeling, some authors focus on modeling neural mechanisms using electronic circuits. Joshi et al. (2011), Irizarry-Valle et al. (2013), Irizarry-Valle and Parker (2015) present neuromorphic engineering and designed CMOS circuits to model small neural networks extended with astrocytes that modulate excitatory postsynaptic potential.

2.1 Multi–Layer Perceptron with Chaos Glial Network

Ikuta et al. (2010) proposed a concept of artificial astrocytes in artificial neural networks and have written multiple papers regarding this topic. Their proposed idea was to extend MLP with astrocytes on a hidden layer (Fig. 1) using formula 1 for computation of hidden neuron's output.

$$h_i(t+1) = f(\sum_{j=0}^{n} w_{ij}(t)x_j(t) + \alpha\Psi_i(t)) \quad (1)$$

Activation of hidden layer is determined by linear combination of weights and input from a previous layer summed with an astrocytic output, $\Psi_i(t)$, multiplied by weight α (shared amongst all astrocytes). Output for a single astrocyte is given by formulas 2 and 3.

$$\Psi_i(t) = \sum_{k=-m}^{m} \beta^{|k|}\psi_{i+k}(t) \quad (2)$$

$$\psi_i(t+1) = \begin{cases} \frac{2\psi(t)+1-A}{1+A}, & (-1 \le \psi(t) \le A) \\ \frac{-2\psi(t)+1+A}{1-A}, & (A < \psi(t) \le 1) \end{cases} \quad (3)$$

where activation of i-th astrocyte, $\Psi_i(t)$, is a sum of m neighboring astrocytes, $\psi_i(t)$, with exponentially attenuating weight by factor $0 < \beta < 1$. Biological motivation using these formulas is that it is known astrocytes generate spontaneous Ca^{2+} oscillations (formula 3) that are propagated throughout glial syncytium (formula 2).

To assess performance of proposed model authors chose well-known benchmark *two-spiral problem* depicted by Fig. 2. This problem cannot be easily solved by standard MLP due to large number of local minima. Architecture of the proposed MLP consisted of two hidden layers with structure 2–20–40–1 with astrocytes extending the second layer exclusively using parameters $\beta = 0.8$ and $m = 5$. The model was trained using standard gradient descent algorithm – *backpropagation*.

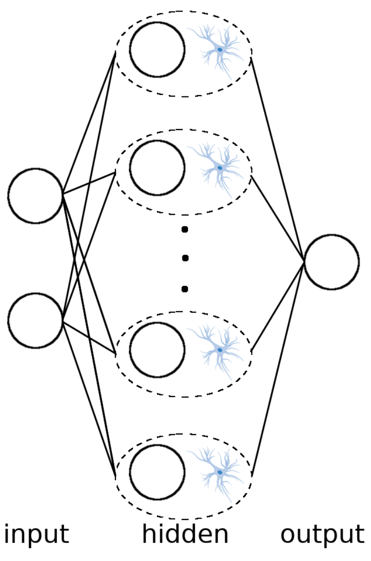

Fig. 1: Architecture of the proposed model. MLP with artificial astrocytes on a hidden layer.

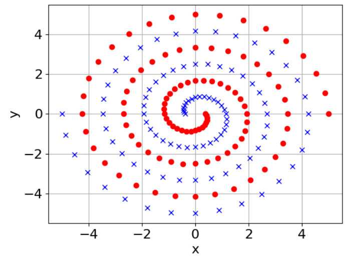

Fig. 2: Two-spiral problem: assigning every point (x, y) to class $\{0, 1\}$.

The authors compared performance of conventional MLP, MLP with *random noise* and proposed MLP (with *chaotic noise*) using *mean squared error*. Proposed model yielded best results followed by MLP with random noise and conventional MLP.

2.2 Multi–Layer Perceptron with Impulse Glial Network

Ikuta et al. (2011) continued in the concept of artificial astrocytes, but instead of implementing chaotic oscillations they introduced *active* astrocytes that listen to and regulate neural activity. Formula 3 was substituted with formula 4.

$$\psi_i(t+1) = \begin{cases} 1, & \theta_n < h_i(t) \wedge \theta_g > \psi_i(t) \\ \gamma\psi_i(t), & \text{otherwise} \end{cases} \quad (4)$$

with 3 new parameters introduced: θ_n is astrocyte's activation threshold, θ_g is astrocyte's refractory period and γ is attenuation factor. Astrocyte generates 1 only when has recoved from refractory period and neuron's output overpasses manually chosen constant threshold.

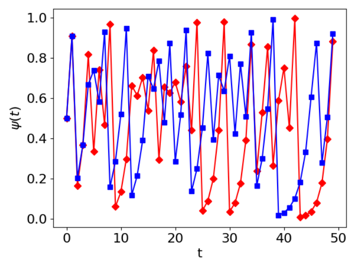

Fig. 3: Two time series used for evaluating performance of model. Task is to assign 4 adjacent values $(\psi(t), \psi(t+1), \psi(t+2), \psi(t+3))$ to classes $\{0, 1\}$.

The problem used for evaluating performance of this model was classification of 4 adjacent values into 2 time series (Fig. 3). The architecture of all 4 models was 4-10-1 and they were trained using backpropagation algorithm. Using metric MSE for estimating classification errors yielded in results displayed in Tab. 1.

Model	avg. MSE
Conventional	0.0351
Random Noise	0.0111
Chaotic Noise	0.0074
Impulse Glia	0.0053

Tab. 1: Performance of 4 models in classification task on time series. Conventional MLP yielded worst results and proposed model with impulse glia yielded best results.

2.3 Astrocyte-driven synaptic plasticity

Concept of synaptic plasticity driven by artifical astrocytes was researched by Alvarellos-González et al. (2012). They extended every neuron (including input and output layers) with astrocyte controlling its synaptic plasticity by counting how many times neuron fired for last k times:

$$r_j(t) = \sum_{i=0}^{k-1} u(x_j(t-i))$$

where $x_j(t)$ is an output of j-th neuron and $u(x_j(t))$ is defined as:

$$u(x_j(t)) = \begin{cases} -1, & x_j(t) \leq 0 \\ 1, & x_j(t) > 0 \end{cases}$$

Synaptic weights are changed accordingly to rules:

$$w_i(t+\Delta t) = w_i(t) + \Delta w_i(t)$$

$$\Delta w_i(t) = |w_i(t)| z(t)$$

$$z(t) = \begin{cases} a, & r_j(t) = \mu \\ b, & r_j(t) = -\mu \end{cases}$$

Parameters a, b, and μ were heuristically chosen. Authors proposed several rules of synaptic plasticity based upon this idea, but we are not listing them all.

Authors evaluated performance of the model trained using proposed rules on 4 different problems and confirmed that model with astrocytes (NGN) was able to learn problems more accurately than identical model without astrocytes (NN), but it highly depended on complexity of selected problem. In 3 cases (amongst 4) NGN was superior to NN. It is questionable why authors did not choose backpropagation algorithm for training NN model, but decided for genetic algorithm which is known to be less effective in training neural networks.

Since algorithm requires parameters a, b, and μ that need to be chosen manually for every individual problem, Mesejo et al. (2015) proposed technique based on evolutionary algorithms and implemented proof of concept that automatically searches for optimal values of parameters.

3 Optimizing astrocyte weight

In our research we were inspired by work Ikuta et al. (2010) described in Section 2.2. We have chosen MLP extended by impulse astrocytes at hidden layer. To assess performance of our model we focused on two-spiral problem (Fig. 2) using architecture 2–20–1. For computation of hidden layer's output we used slightly modified version of formula 1:

$$h_i(t+1) = f(\sum_{j=0}^{n} w_{ij}(t) x_j(t) + \alpha_i \Psi_i(t))$$

Notice α was substituted by α_i. For activation of astrocytes we used formulas 2 and 4. Parameter values were: $\eta = 0.01$, $m = 20$, $\beta = 0.5$, $\theta_n = 0.6$, $\theta_g = 10^{-4}$, $\gamma = 0.5$. Since loss function is defined as:

$$E(w) = \frac{1}{2} \sum_{p} (d^{(p)} - y(x^{(p)}))^2$$

parameter α_i can be optimized:

$$\Delta \alpha_i = -\eta \frac{\partial E(w)}{\partial \alpha_i}$$

$$\Delta \alpha_i = -\eta \Big(\sum_j \frac{\partial E}{\partial y_j} \frac{\partial y_j}{\partial net_j} \frac{\partial net_j}{\partial h_i} \Big) \frac{\partial h_i}{\partial net_i} \frac{\partial net_i}{\partial \alpha_i}$$

$$\Delta \alpha_i = -\eta \Big(\sum_j \overbrace{(t_j - y_j) y_j (1 - y_j)}^{\delta_j} w_{ji} \Big) h_i (1 - h_i) \Psi_i$$

$$\Delta \alpha_i = -\eta \overbrace{\Big(\sum_j \delta_j w_{ji} \Big) h_i (1 - h_i)}^{\delta_i} \Psi_i$$

$$\Delta \alpha_i = -\eta \delta_i \Psi_i$$

We implemented proof of concept algorithm to computationally evaluate performance with results illustrated in Fig. 4.

4 Conclusion

Understanding the role of astrocytes and neuron–astrocyte interactions are essential for understanding the brain. Computational models in this context are inevitable since they allow us to test correctness of our knowledge, specified hypotheses and propose means for prediction of certain behavior. In this work we focused

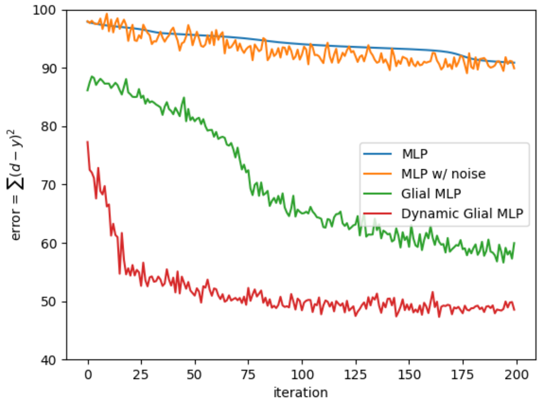

Fig. 4: Simulations of 4 models on two-spiral problem. Conventional model (blue) and model with gaussian noise (orange) were not able to escape local minima, but models with artifical astrocytes (green and red) were. Dynamic update of α_i during training (red) yielded lowest error (best performance).

on existing connectionist models that incorporates artificial astrocytes into MLP. We showed how astrocytic noise works better than gaussian noise and how synaptic plasticity could be driven by astrocytes. We proposed technique for optimizing astrocyte weight that yields better results than the original model. Since all presented techniques have been shown to help avoiding being stuck in local minima, it is definitely possible to attempt applying them to different models that have this tendency. Therefore future research could focus on integrating these techniques into recurrent, self–organizing or spiking models.

5 Acknowledgment

This work was supported by the grant APVV-0668-12 and KEGA grant 017UK-4/2016.

References

Alvarellos-González, A., Pazos, A. and Porto-Pazos, A. B. (2012). Computational models of neuron-astrocyte interactions lead to improved efficacy in the performance of neural networks. *Computational and Mathematical Methods in Medicine*, 2012.

Brightman, M. and Reese, T. (1969). Junctions between intimately apposed cell membranes in the vertebrate brain. *Journal of Cell Biology*, 40(3):648–677.

Hilgetag, C. C. and Barbas, H. (2009). Are there ten times more glia than neurons in the brain? *Brain Structure and Function*, 213(4-5):365–366.

Ikuta, C., Uwate, Y. and Nishio, Y. (2010). Chaos glial network connected to multi-layer perceptron for solving two-spiral problem. In *Proceedings of 2010 IEEE International Symposium on Circuits and Systems (ISCAS)*, pages 1360–1363. IEEE.

Ikuta, C., Uwate, Y. and Nishio, Y. (2011). Performance and features of multi-layer perceptron with impulse glial network. In *Proceedings of the International Joint Conference on Neural Networks*, pages 2536–2541. IEEE.

Irizarry-Valle, Y. and Parker, A. C. (2015). An astrocyte neuromorphic circuit that influences neuronal phase synchrony. *IEEE Transactions on Biomedical Circuits and Systems*, 9(2):175–187.

Irizarry-Valle, Y., Parker, A. C. and Joshi, J. (2013). A cmos neuromorphic approach to emulate neuro-astrocyte interactions. In *International Joint Conference on Neural Networks*, pages 1–7.

Joshi, J., Parker, A. C. and Tseng, K.-C. (2011). An in-silico glial microdomain to invoke excitability in cortical neural networks. In *IEEE International Symposium of Circuits and Systems*, pages 681–684.

Mesejo, P., Ibánez, O., Fernández-Blanco, E., Cedrón, F., Pazos, A. and Porto-Pazos, A. B. (2015). Artificial neuron–glia networks learning approach based on cooperative coevolution. *International Journal of Neural Systems*, 25(04):1550012.

Murray, A. F. and Edwards, P. J. (1994). Enhanced mlp performance and fault tolerance resulting from synaptic weight noise during training. *IEEE Transactions on Neural Networks*, 5(5):792–802.

Orkand, R., Nicholls, J. and Kuffler, S. (1966). Effect of nerve impulses on the membrane potential of glial cells in the central nervous system of amphibia. *Journal of Neurophysiology*, 29(4):788–806.

Oschmann, F., Berry, H., Obermayer, K. and Lenk, K. (2017). From in silico astrocyte cell models to neuron-astrocyte network models: A review. *Brain Research Bulletin*.

Volman, V., Bazhenov, M. and Sejnowski, T. (2012). Computational models of neuron-astrocyte interaction in epilepsy. *Frontiers in Computational Neuroscience*, 6:58.

Wade, J., Kelso, S., Crunelli, V., McDaid, L. J. and Harkin, J. (2014). *Biophysically based Computational Models of Astrocyte ∼ Neuron Coupling and their Functional Significance*. Frontiers E-books.