Investigating the Role of Astrocyte Units in a Feedforward Neural Network

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Abstract. Current research in neuroscience has begun to shift perspective from neurons as sole information processors to including the astrocytes as equal and cooperating units in this function. Recent evidence sheds new light on astrocytes and presents them as important regulators of neuronal activity and synaptic plasticity. In this paper, we present a multi-layer perceptron (MLP) with artificial astrocyte units which listen to and regulate hidden neurons based on their activity. We test the behavior and performance of this bio-inspired model on two classification tasks, N-parity problem and the two-spirals problem and show that proposed models outperform the standard MLP. Interestingly, we have also discovered multiple regimes of astrocyte activity depending on the complexity of the problem.

Keywords: Glial cells · Astrocytes · MLP · Classification
Computational model

1 Introduction

Glial cells, predominantly astrocytes, have gained a lot of attention in neuroscience during the last few decades, as compelling evidence has shown that these cells are no longer considered as passive and supportive but are actively involved in neuronal regulation and synaptic plasticity [1,12]. The classical view on astrocytes supports the idea that they are inevitable in the development of the central nervous system, providing metabolic and physical support to other neural cells, or maintaining homeostasis. It was assumed that astrocytes were not able to generate actions potentials similar to neurons, or be involved in brain functions such as information transfer and processing, learning, and plasticity, i.e. functions attributed solely to neurons.

However, recent research has challenged this view as it was discovered that astrocytes were characterized as having resting membrane potential of $\sim -80\,\mathrm{mV}$, pairing ~ 1.4 astrocytes for every neuron in the human cortex [3] and encapsulating $\sim 10^5$ synapses [5]. This led to a novel concept of an intimate connection between neurons and astrocytes named the *tripartite synapse*. Moreover, astrocytes release gliotransmitters to local neurons and propagate Ca^{2+} waves using

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a cellular network called *glial syncytium*, although the signalization occurs on a much slower time scale ranging from seconds to minutes, as opposed to neurons whose time scale is milliseconds. This implies the existence of a bidirectional communication between astrocytes and neurons whose importance is still not well understood.

Still, it is assumed that the brain function and possibly higher cognition emerge from the coordinated activity of astrocytes and neurons in neuron–glia networks [11]. A better understanding of astrocyte–neuron coupling may lead to providing building blocks for studying the regulatory capability of astrocytic networks on a larger scale. Computational models of neural networks extended with artificial glia may not only be used as an interesting novel concept, but mainly to provide space for hypotheses for the potential roles of glial cells in biological neuronal circuits and networks.

In this paper we propose a model of a MLP extended with artificial astrocytes whose role is to regulate neuronal activity. For evaluating the model performance we chose the classification task using two datasets: N-parity and two spirals. The paper is organized as follows. Section 2 includes the related work. In Sect. 3, we describe various versions of the investigated model. In Sect. 4, we provide the experimental results. Section 5 concludes the paper.

2 Related Work

In computational neuroscience two modeling paradigms have so far been considered: (1) biophysical with the focus on low–level physical and chemical properties of a biological system or (2) connectionist which does not try to model every single aspect of a system, but instead focuses on abstractions. Despite the plethora of biophysical models of astrocytes, connectionist modeling is still in a pre-mature state.

The concept of artificial astrocytes in connectionist systems was first introduced in [6] where authors augmented the hidden layer of an MLP with an astrocytic network whose function was to generate chaotic noise according to the given tent map formula as a means of avoiding local minima during gradient optimization. On the two-spirals problem the model achieved better performance than the regular MLP. Later, the same authors presented multiple works including impulse astrocytes with active listening and regulation of neurons based on their activity [7], Hopfield network augmented with astrocytes [9], or neurogenesis driven by astrocytes [8].

Similar approach was taken in [13] and [2] where instead of modeling the neuronal regulation, the authors focused on modeling synaptic plasticity driven solely by astrocytes. Using an MLP with combination of evolutionary algorithms they showed that the model with artificial astrocytes was superior to the model without them. Using computer simulations they demonstrated that the model was able to learn various problems despite the fact that no gradient-based method was used for training neural networks.

Finally, in [10], the authors presented a model, SONG-Net, that combines an MLP, a self-organizing map (SOM) and neuron–glial interactions. By evaluating

the performance on four tasks, they showed that the proposed model achieved faster convergence up to twelve times with a lower error rate. However, the authors did not present glia as individual functional units, but instead they were used only as an inspiration for the concept of neuronal regulation.

3 Proposed Models

Here we present multiple models, all based on an MLP combined with artificial astrocytes. We start with a simplest model to allow faster in–depth exploration, and we gradually move toward adding more complex, yet biologically plausible mechanisms.

3.1 A-MLP

Since the human cortex contains on average 1.4 astrocytes for each neuron, we simplify this notion and present a model with the ratio of astrocyte to neuron being 1:1. Inspired by [7] we combine the hidden layer of an MLP with impulse astrocytes that listen to and modulate neuronal activity of hidden neurons (Fig. 1).

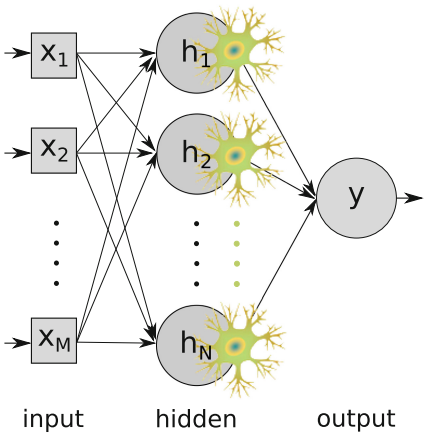

Fig. 1. Basic MLP architecture with astrocyte units (A-MLP). Each hidden neuron is paired with an astrocyte that listens to and regulates its regime based on activity. Since we consider binary classification problems, only one output unit is used.

The output of i-th hidden neuron is given by the following formula

$$h_i(t+1) = f(\sum_{j=0}^{M} w_{ij} x_j(t) + \alpha \psi_i(t)) \tag{1}$$

where the activation function is

$$f(net) = \frac{1}{1 + \exp(-net)} \tag{2}$$

and the astrocyte activity is modified as

$$\psi_i(t) = \begin{cases} 1, & \text{if } \theta < h_i(t-1) \\ \gamma\psi_i(t-1), & \text{otherwise} \end{cases} \tag{3}$$

Each astrocyte contributes, with a weight α, to the activity of the hidden neuron (Eq. 1). When the neuron output exceeds the given threshold θ, the astrocyte activation is set to 1 and then starts to decay by a factor γ, where $0 < \gamma < 1$.

Note that the model consists of three free hyperparameters whose optimal values have to be found experimentally. Since each problem requires a different set of optimal parameters, finding them requires time-intensive computations. We try to solve these issues by replacing constant parameters with modifiable versions.

3.2 A-MLP(α)

Traditionally in supervised model learning, the neuron weights are updated using a gradient descent method, better known as error backpropagation algorithm. Since the astrocytic weight in Eq. 1 can be treated as any other weight, we can apply the same optimization method for its update (derivation of the formula is provided in appendix).

Next, instead of using a single mutual weight for all astrocytes, we equip each astrocyte unit with an individual weight. The activation rule for the hidden unit then becomes

$$h_i(t+1) = f(\sum_{j=0}^{M} w_{ij}x_j(t) + \alpha_i\psi_i(t)) \tag{4}$$

3.3 A-MLP(θ)

Since we cannot directly update the parameter θ (Eq. 3) using a gradient-based method, we propose an unsupervised learning rule. It is relatively common that during training some neurons may get trapped in one of the two extremes, by becoming either dead or permanently active. The weight update of such neurons becomes problematic, because the gradient is close to zero and no errors would propagate through a dead neuron, therefore no update would occur. On the other hand, weights might grow into large values affecting other neurons in the network, making the model unstable.

The same issue may happen in artificial astrocytes when the threshold θ is set too low, making the astrocytes fire all the time, or too high, preventing the neighboring neurons from exceeding the required activation. Moreover, since

each neuron in the neural network develops its own role in the classification task, single shared θ for all neurons may become more of a burden than benefit.

To solve these problems, we propose an individual θ_i for each astrocyte and two variations of an update rule. In order to stabilize the astrocytic regime, we can set the threshold θ either directly to the mean value $\langle . \rangle_t$ (Eq. 5) of an astrocyte unit or only shift the threshold slightly closer to the mean value (Eq. 6) using the learning speed η_θ. This forces the astrocyte to move only within its mean values avoiding the critical values of 0 and 1. With a higher θ it becomes harder for the neuron to overpass, thus the activity decays and vice versa. Hence, the update rules are

$$\theta_i(t+1) = \langle \psi_i(t) \rangle_t \tag{5}$$

and

$$\theta_i(t+1) = \theta_i(t) + \eta_\theta(\langle \psi_i(t) \rangle_t - \theta_i(t)) \tag{6}$$

introducing another free parameter, namely the length of an averaging window.

3.4 A-MLP(γ)

Hyperparameter γ can be updated based on the same principle as explained in the previous section. This time we update γ to achieve inverse correlation with the mean value of the astrocytic activity

$$\gamma_i(t+1) = 1 - \langle \psi_i(t) \rangle_t \tag{7}$$

$$\gamma_i(t+1) = \gamma_i(t) + \eta_\gamma(1 - \langle \psi_i(t) \rangle_t - \gamma_i(t)) \tag{8}$$

Higher values of γ are achieved during a lower activity, thus a hypo-excited astrocyte holds its activation value for a longer period. On the other hand, lower γ triggers faster output decay forcing the astrocyte to avoid excessive simulation.

3.5 A-MLP(γ, θ), A-MLP(α, γ, θ)

Finally, the last two models are simple combinations of previous ideas. A-MLP (γ, θ) combines models with dynamic θs and γs and A-MLP(α, γ, θ) includes dynamic αs as well.

4 Experiments

We assess the performance of all six proposed models and standard MLP (without astrocyte units) as a baseline, on two difficult classification tasks: (1) N-parity problem and (2) two spirals problem. All results are averaged over 100 simulations with different initial setups. The learning rate in backpropagation algorithm is set to $\eta = 0.1$.

4.1 N-parity Problem

The task is to determine whether a binary input vector has even or odd number of ones. More formally, an input vector has the form $[x_1, \ldots, x_N], x_i = \{0, 1\}$ and the target $y = (1 + \sum_{i=1}^{N} x_i) \mod 2$. Since the problem is notoriously difficult to generalize to unseen patterns for machine learning algorithms, we train the models on full dataset (no train/test split) whose total size is 2^N.

Starting with MLP, we chose the hidden layer with N neurons (a higher amount did not yield better results) and output layer of only single neuron ($0 =$ odd input vector, $1 =$ even input vector). Proposed models with astrocyte units had the following values for fixed hyperparameters: $\alpha = -0.5, \gamma = 0.5, \theta = 0.5$ (previously found using the grid search). In Table 1 we present performance of all models and although we see models with astrocyte units lead on average to better performance, the differences are not statistically significant ($p > 0.1$).

Next, in order to get insight into learned parameters, we displayed the distributions of astrocyte activities (shown in Fig. 2). It can be seen that astrocytes develop various regimes depending on the problem complexity. With lower N it is possible to clearly detect N astrocyte regimes, but with higher N the profiles gradually lose their multimodality, albeit remaining non uniformly distributed.

Table 1. Mean squared error (MSE) + standard deviation of 100 instances on three parity problems trained for 10000 epochs. Models with astrocyte units yield lower error rate although no statistical significance was found. In each task, the best model is denoted with $*$.

Model	4-parity	6-parity	8-parity
MLP	0.081 ± 0.060	0.065 ± 0.035	0.046 ± 0.070
A-MLP	0.083 ± 0.086	$0.059 \pm 0.034*$	0.039 ± 0.023
A-MLP(α)	0.080 ± 0.065	0.072 ± 0.054	0.073 ± 0.069
A-MLP(θ)	0.083 ± 0.075	0.065 ± 0.036	$0.037 \pm 0.021*$
A-MLP(γ)	0.087 ± 0.065	0.062 ± 0.034	0.042 ± 0.026
A-MLP(γ, θ)	$0.074 \pm 0.051*$	0.063 ± 0.055	0.042 ± 0.027
A-MLP(α, γ, θ)	0.092 ± 0.072	0.078 ± 0.056	0.056 ± 0.028

4.2 Two-Spirals Problem

The two spirals consist of two interleaved sets of points in 2D space (Fig. 3). The problem is, given point (x, y), to decide whether it belongs to the first or the second spiral. This is considered a complex nonlinear problem and hard for a standard MLP due to a high number of local minima which are generally rather problematic for gradient-based models.

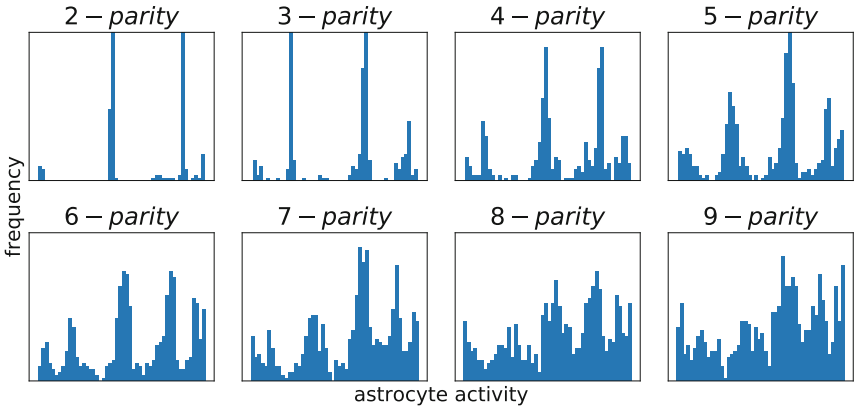

Fig. 2. Distributions of astrocyte activity (across 100 simulations) after being fully trained on a parity problem. With lower N it is possible to detect N peaks assuming that each astrocyte handles a single bit from an input vector. On the other hand, with higher N, the peaks become less visible.

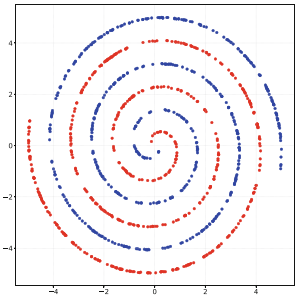

Fig. 3. Two-spirals problem where the task is to separate the interleaved classes.

For the simulations we firstly found optimal hyperparameter values for MLP and then used them in models with astrocyte units. We used $N = 30$ hidden neurons (more units did not produce better results), 5000 training epochs and train/test dataset split in ratio 80:20. For models with astrocytes we found optimal hyperparameters using grid search (presented in Fig. 4) and hence used the values: $\alpha = -0.1$, $\gamma = 0.5$, $\theta = 0.1$.

Results averaged over 100 simulations are in Table 2 with A-MLP(γ, θ) being the best model yielding 50% lower error rate compared to the standard MLP. Similarly we looked at astrocyte activities of the fully trained network and observed normal distribution shown in Fig. 6.

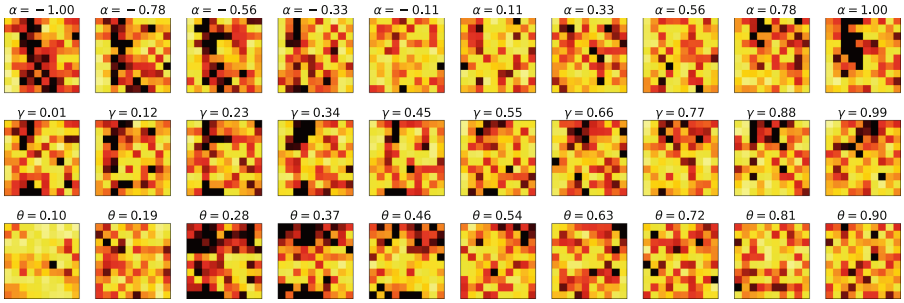

Fig. 4. Grid search for optimal values of hyperparameters. Each heatmap uses a fixed single parameter (shown in the title) and displays all combinations for the other two parameters. Each cell in every heatmap is averaged over 5 simulations with lighter color denoting better performance.

Table 2. Mean-squared error + standard deviation over 100 instances on the two-spirals task trained for 5000 epochs. The best model, A-MLP(γ, θ), yields 50% lower error rate compared to the MLP with statistical significance ($p < 0.001$) (Fig. 5).

Model	Train	Test
MLP	0.075 ± 0.067	0.094 ± 0.066
A-MLP	0.073 ± 0.067	0.088 ± 0.068
A-MLP(α)	0.050 ± 0.049	0.078 ± 0.050
A-MLP(θ)	0.034 ± 0.045	0.049 ± 0.046
A-MLP(γ)	0.068 ± 0.065	0.085 ± 0.063
A-MLP(γ, θ)	$0.030 \pm 0.035*$	$0.051 \pm 0.041*$
A-MLP(α, γ, θ)	0.060 ± 0.051	0.095 ± 0.051

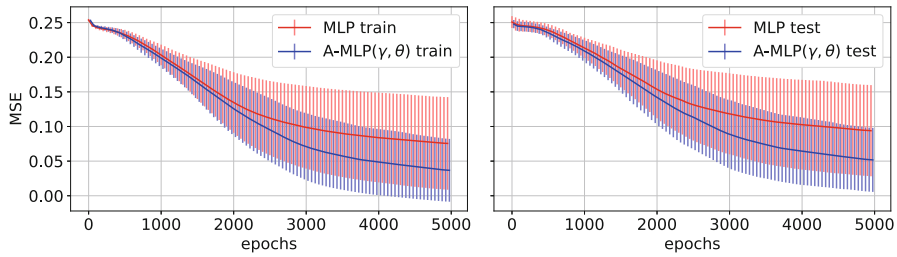

Fig. 5. Performance of the best model, A-MLP(γ, θ), compared to MLP on both training and testing sets.

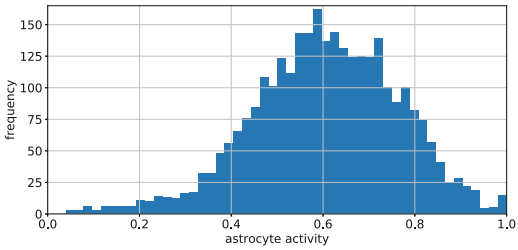

Fig. 6. Normal distribution of astrocyte activity ($N = 30$) at the end of training, accumulated over 100 simulations.

5 Conclusion

Inspired by [7] and the recent findings from biological research of astrocyte physiology and their interactions with surrounding neurons, we proposed artificial astrocyte units to be integrated in a MLP.

It is known that astrocytes in CNS form networks in which they communicate using Ca^{2+} waves whose purpose according to current knowledge is to regulate neuronal activity and synaptic plasticity. In this paper we focused exclusively on neuronal regulation using separate astrocytes each maintaining a single neuron. Astrocytes contribute in neuronal summation formula (Eq. 4) weighted by the factor α_i which was either constant or dynamic. However, the dynamic change of a weight along the negative gradient of the loss function does not always provide better results (as in N-parity problem). We also proposed two methods for dynamic update of both the astrocyte threshold and the decay (Eqs. 5–8) with the second formula performing better than the first one which we used in all our simulations.

We chose two classification problems, N-parity and two spirals, which are known to be rather problematic for machine learning algorithms, so we used them for analysis of the performance and behavior of our models. For both problems we first selected an MLP with optimal parameters (the number of hidden neurons, the learning rate, initial weight distribution) and then used them in models with astrocyte units. The results obtained for N-parity did not outperform MLP, assuming that all models already converged to the global minimum. However, for the two spirals all our models performed better in terms of the lower errors with statistical significance ($p < 0.001$). Both problems developed unique astrocyte regimes in terms of output distributions whose shape depended on the number of astrocytes in case of N-parity problem and was gaussian in the two spirals task. Understanding of this phenomenon requires further investigations.

For our future research we would like to focus on a different set of problems trying to explain why astrocyte regimes develop and how important they are for the given problem. We only focused on feedforward models, but it makes sense to apply the very same idea to recurrent neural networks. Another issue worth investigation would be to adjust the dynamics of astrocytes. In our models, astrocyte parameters were updated at the same speed as weights, but it is known

that the dynamics of the biological astrocytes is much slower [4]. Last but not least, since we only focused on modulations of single neurons, we would like to connect astrocytes within the syncytium and incorporate their role in synaptic plasticity.

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Appendix: Derivation of the update formula

Here we derive formula for stochastic (online) update of astrocyte weights α_i in models A-MLP(α) and A-MLP(α, θ, γ). The goal is to minimize the loss function $E(w) = 1/2(d - y(x))^2$, by moving the astrocytic weights along the negative gradient, i.e. $\Delta\alpha_i = -\partial E(w)/\partial\alpha_i$. Since E is differentiable with respect to α_i, we can write using the chain rule,

$$\Delta\alpha_i = -\frac{\partial E}{\partial y}\frac{\partial y}{\partial net_y}\frac{\partial net_y}{\partial h_i}\frac{\partial h_i}{\partial net_{hi}}\frac{\partial net_{hi}}{\partial \alpha_i} \tag{9}$$

$$\Delta\alpha_i = -\overbrace{(d - y(x))y(x)(1 - y(x))}^{\delta_y} w_{yh_i} h_i(1 - h_i)\psi_i \tag{10}$$

$$\Delta\alpha_i = -\overbrace{\delta_y w_{yh_i} h_i(1 - h_i)}^{\delta_i}\psi_i \tag{11}$$

which yields the final formula:

$$\Delta\alpha_i = -\delta_i\psi_i \tag{12}$$

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