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Code repository

A reference implementation of

→ *Interaction between cognitive and motor cortico-basal ganglia loops during decision making: a computational study*, M. Guthrie, A. Leblois, A. Garenne, and T. Boraud, Journal of Neurophysiology, 109, 2013.

Introduction

We propose a reference implementation of [1] that introduces an action selection mechanism in cortico-basal ganglia loops based on a competition between the positive feedback, direct pathway through the striatum and the negative feedback, hyperdirect pathway through the subthalamic nucleus. The original implementation was made in Delphi (Object Pascal) whose sources are available on request to any of the author of the original article. We have used these sources to disambiguate ambiguous and missing information in the original article. The reference implementation we propose has been coded in Python for ease of reading and Cython for performances because the main result includes a batch of 250 experiments over 120 trials that would be too slow for regular Python scripts.

Methods

We used the description of the model in the original article as well as the sources of the model (requested from author) that are made of a hundred files and 6,000 lines of Delphi for the main source. We have been unable to compile this original implementation but we were able to run the provided Windows executable. We found some factual errors in the original article that have been corrected in this implementation. The initialization of weights are defined in two different parts of the paper. First on page 3030 (second column) *"Weights were initialized to a Gaussian distribution with a mean of 0.5 and a SD of 0.005 at the start of each simulation…"*, then on page 3031 in the caption of figure 4, *"All synaptic weights were initialized to 0.5"*. It happened that both definitions are right but do not address the same projections. Cortico-striatal synaptic weights use Gaussian distribution while all other weights are set to 0.5. Furthermore, the Boltzmann equation given in the original paper uses a . instead of + between first term and second term.

One notable modification in our implementation is the reinforcement learning rule that has been greatly simplified. Original authors have been using quite a complex algorithm for ensuring that *"corticostriatal weights are bounded by a sigmoidal transfer function to represent physical constraints on synaptic growth with an absolute maximum of 0.75 and an absolute minimum of 0.25."*. This algorithm is not described in the article, but from sources, it appears that it is based on the estimation of the weight gradient along the sigmoid. We use instead an Oja-like rule given in the *Synapse* table.

We provide below the formal description of the model according to the proposition of Nordlie et al. [2] for reproducible descriptions of neuronal network models.

Table 1: Model description following [2] prescription.

Table	Description
Populations	Cortex (motor, associative & cognitive), Striatum (motor, associative & cognitive), GPi (motor & cognitive), STN (motor & cognitive), Thalamus (motor & cognitive)
Topology	–
Connectivity	One to one, one to many (divergent), many to one (convergent)
Neuron model	Dynamic rate model
Channel model	–
Synapse model	Linear synapse
Plasticity	Reinforcement learning rule
Input	External current in cortical areas (motor, associative & cognitive)
Recordings	Firing rate & performances

Table 2: Populations

Name	Elements	Size	Threshold	Noise	Initial state	τ
Cortex motor	Linear neuron	1×4	-3	1.0%	0.0	10
Cortex cognitive	Linear neuron	4×1	-3	1.0%	0.0	10
Cortex associative	Linear neuron	4×4	-3	1.0%	0.0	10
Striatum motor	Sigmoidal neuron	1×4	0	0.1%	0.0	10
Striatum cognitive	Sigmoidal neuron	4×1	0	0.1%	0.0	10
Striatum associative	Sigmoidal neuron	4×4	0	0.1%	0.0	10
GPi motor	Linear neuron	1×4	+10	3.0%	0.0	10
GPi cognitive	Linear neuron	4×1	+10	3.0%	0.0	10
STN motor	Linear neuron	1×4	-10	0.1%	0.0	10
STN cognitive	Linear neuron	4×1	-10	0.1%	0.0	10
Thalamus motor	Linear neuron	1×4	-40	0.1%	0.0	10
Thalamus cognitive	Linear neuron	4×1	-40	0.1%	0.0	10
Values (V_i)	Scalar	4	–	–	0.5	-

Table 3: Connectivity

Source	Target	Pattern	Weight	Gain	Plastic
Cortex motor	Thalamus motor	$(1, i) \rightarrow (1, i)$	1.0	0.4	No
Cortex cognitive	Thalamus cognitive	$(i, 1) \rightarrow (i, 1)$	1.0	0.4	No

Source	Target	Pattern	Weight	Gain	Plastic
Cortex motor	STN motor	$(1, i) \rightarrow (1, i)$	1.0	1.0	No
Cortex cognitive	STN cognitive	$(i, 1) \rightarrow (i, 1)$	1.0	1.0	No
Cortex motor	Striatum motor	$(1, i) \rightarrow (1, i)$	0.5	1.0	No
Cortex cognitive	Striatum cognitive	$(i, 1) \rightarrow (i, 1)$	0.5	1.0	Yes
Cortex motor	Striatum associative	$(1, i) \rightarrow (., i)$	0.5	0.2	No
Cortex cognitive	Striatum associative	$(i, 1) \rightarrow (i, .)$	0.5	0.2	No
Cortex associative	Striatum associative	$(i, j) \rightarrow (i, j)$	0.5	1.0	No
Thalamus motor	Cortex motor	$(1, i) \rightarrow (1, i)$	1.0	1.0	No
Thalamus cognitive	Cortex cognitive	$(i, 1) \rightarrow (i, 1)$	1.0	1.0	No
GPi motor	Thalamus motor	$(1, i) \rightarrow (1, i)$	1.0	-0.5	No
GPi cognitive	Thalamus cognitive	$(i, 1) \rightarrow (i, 1)$	1.0	-0.5	No
STN motor	GPi motor	$(1, i) \rightarrow (1, i)$	1.0	1.0	No
STN cognitive	GPi cognitive	$(i, 1) \rightarrow (i, 1)$	1.0	1.0	No
Striatum cognitive	GPi cognitive	$(i, 1) \rightarrow (i, 1)$	1.0	-2.0	No
Striatum motor	GPi motor	$(i, 1) \rightarrow (i, 1)$	1.0	-2.0	No
Striatum associative	GPi motor	$(., i) \rightarrow (1, i)$	1.0	-2.0	No
Striatum associative	GPi cognitive	$(i, .) \rightarrow (i, 1)$	1.0	-2.0	No

Table 4: Neuron Model (1)

Linear neuron	
Type	Rate model
Membrane Potential	$\tau dV/dt = -V + I_{syn} + I_{ext} - h$ $U = max(V, 0)$

Table 5: Neuron Model (2)

Sigmoidal neuron	
Type	Rate model
Membrane Potential	$\tau dV/dt = -V + I_{syn} + I_{ext} - h$ $U = V_{min} - (V_{max} - V_{min})/\left(1 + e^{\frac{V_h - V}{V_c}}\right)$ $V_{min} = 1,\ V_{max} = 20,\ V_h = 16,\ V_c = 3$

Table 6: Synapse

Linear synapse	
Type	Weighted sum
Output	$I^B_{syn} = \sum_{A \in sources}(G_{A \rightarrow B} W_{A \rightarrow B} U_A)$

Table 7: Plasticity

Reinforcement learning	
Type	Delta rule
Delta	$\Delta W_{A \rightarrow B} = \alpha \times PE \times U_B \times S$ $S = (W_{A \rightarrow B} - W_{min})(W_{max} - W_{A \rightarrow B})$ $PE = Reward - V_i$

Reinforcement learning
$\alpha = 0.02$ if $PE < 0$ (LTD), $\alpha = 0.04$ if $PE > 0$ (LTP)

Table 8: Recordings

Site	Type
Cognitive cortex	Firing rate
Motor cortex	Firing rate
Cortico-striatal projections	Weights

Table 9: Input

Type	Description
Cortical input	A trial is preceded by a settling period (500ms) and followed by a reset period. At time $t = 0$, two shapes are presented in cortical cognitive area ($I_{ext} = 7$ at $\{i_1, i_2\}$) at two different locations in cortical motor area ($I_{ext} = 7$ at $\{j_1, j_2\}$) and the cortical associate area is updated accordingly ($I_{ext} = 7$ at $\{i_1, i_2\} \times \{j_1, j_2\}$)

Table 10: Environment

Resources	Version
OS	OSX 10.10 (yosemite)
Language	Python 2.7.6 (brew installation)
Libraries	Numpy 1.8.1 (pip installation)
	Matplotlib 1.3.0 (pip installation)
	Cython 0.22 (pip installation)

Results

We did not reproduce all analyses of the original article but concentrated our efforts on the main results which are illustrated on figures 4 & 5 in the original article [1].

We first reproduce the activity in the cortical populations during a single trial, prior to learning. Noise has a great influence on the overall dynamic and it is not possible to exactly reproduce figure 4 in the original article without precise information on the underlying random generator(seed). Consequently, we can only report a qualitatively equivalent figure where the most critical feature is the bifurcation in cognitive and motor activities after stimulus onset. Since no learning has occured yet, it is also possible to have the motor decision to occur before the cognitive decision. Figure 1 shows an example of a decision dynamic with an oscillatory regime between time t=0 and time t=500ms that is characteristic of the model.

We also tested the learning capacity of the model by reproducing the same procedure as in the original article (250 experiments, 120 trials) but we used a modified and simpler learning rule (see Plasiticity table) since the original learning rule used a sigmodial transfer function but no actual details were given on how to enforce it.

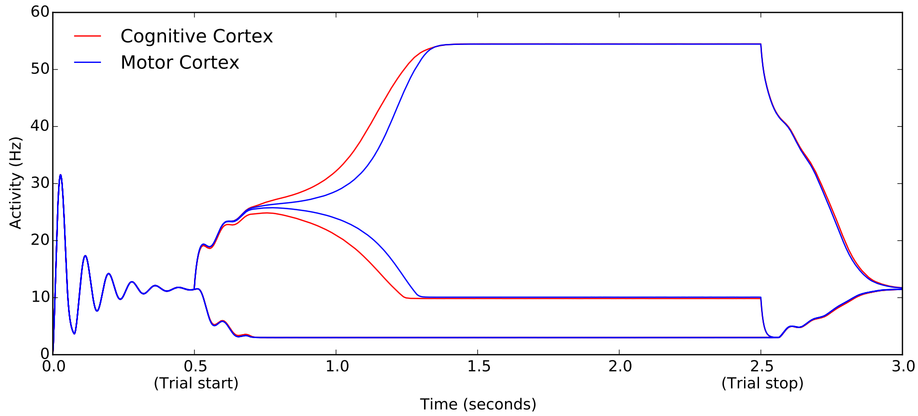

Figure 1: Activity in the cortical population during a single trial of action selection. This is the reproduction of figure 4 in the original article.

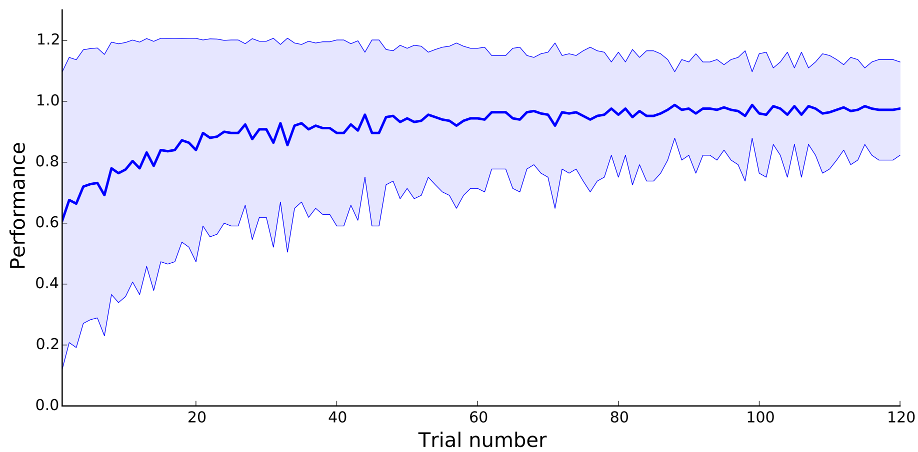

Figure 2: Learning time course over 120 trials, averaged over 250 simulations. The blue filled area indicates the standard devisation of the mean performance.

Conclusion

After some minor corrections and modifications of the original description of the model, we were able to reproduce the original results, confirming the correctness of the original implementation of the model.

References

[1] M. Guthrie et al. "Interaction between cognitive and motor cortico-basal ganglia loops during decision making: a computational study". In: *Journal of Neurophysiology* 109 (2013), pp. 3025–3040. DOI: 10.1152/jn.00026.2013.

[2] E. Nordlie, M. Gewaltig, and H.E. Plesser. "Towards reproducible descriptions of neuronal network models". In: *PLoS Computational Biology* 5.8 (2009), e1000456. DOI: 10.1371/journal.pcbi.1000456.