ReScience C

Topalidou and Rougier 2015

[Re] Interaction between cognitive and motor cortico-basal ganglia loops during decision making: a computational study

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Abstract. We propose 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(12), 2013 that introduces an action selection mechanism in cortico-basal ganglia loops based on a competition between the positive feed- back, 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.

Keywords: python, computational neuroscience

A replication of M. Guthrie, A. Leblois, A. Garenne, and T. Boraud. Interaction between cognitive and motor cortico-basal ganglia loops during decision making: a computational study. In: Journal of Neurophysiology 109.12 (2013)

Cite as: [Re] Interaction between cognitive and motor cortico-basal ganglia loops during decision making: a computational study, M. Topalidou and N.P. Rougier. In: *ReScience C* 1(#1), 2015. **DOI** 10.5072/zenodo.217655.

Code repository at github.com/rougier/model-code – **DOI** 10.5281/zenodo.27944
Data repository at github.com/rougier/model-data – **DOI** 10.5281/zenodo.27944.

Edited by Tiziano Zito – **Reviewed by** Benoît Girard & Mehdi Khamassi – Open Review
Received 09 June 2015 – **Accepted** 12 August 2015 – **Published** 14 August 2015

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Competing Interests: The authors have declared that no competing interests exist

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 hundred files and 6,000 lines of Delphi for the main source. We've been unable to compile this original implementation but we're able to run the provided Windows executable. We found some factual errors in the original article that have been corrected in this implementation. We provide below the formal description of the model according to the proposition of [2] for reproducible descriptions of neuronal network models.

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 1. Model description following [2] prescription.

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

Table 2. Populations

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
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 3. Connectivity

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

Table 4. Neuron Model (1)

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

Table 5. Neuron Model (2)

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

Table 6. Synapse

Reinforcement learning	
Type	Delta rule
Delta	$\Delta W_{A \rightarrow B} = \alpha \times PE \times U_B \times S$
	$S = (W_{A \rightarrow B} - W_{min})(W_{max} - W_{A \rightarrow B})$
	$PE = Reward - V_i$
	$\alpha = 0.02$ if $PE < 0$ (LTD), $\alpha = 0.04$ if $PE > 0$ (LTP)

Table 7. Plasticity

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 8. Input

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

Table 9. Recordings

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)

Table 10. Environment

Results

We did not reproduce all analysis of the original article but concentrate our efforts on the main results which are illustrated on figures 4 & 5 in the original article [1]. We first reproduced 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 test learning capacity of the model by reproducing the

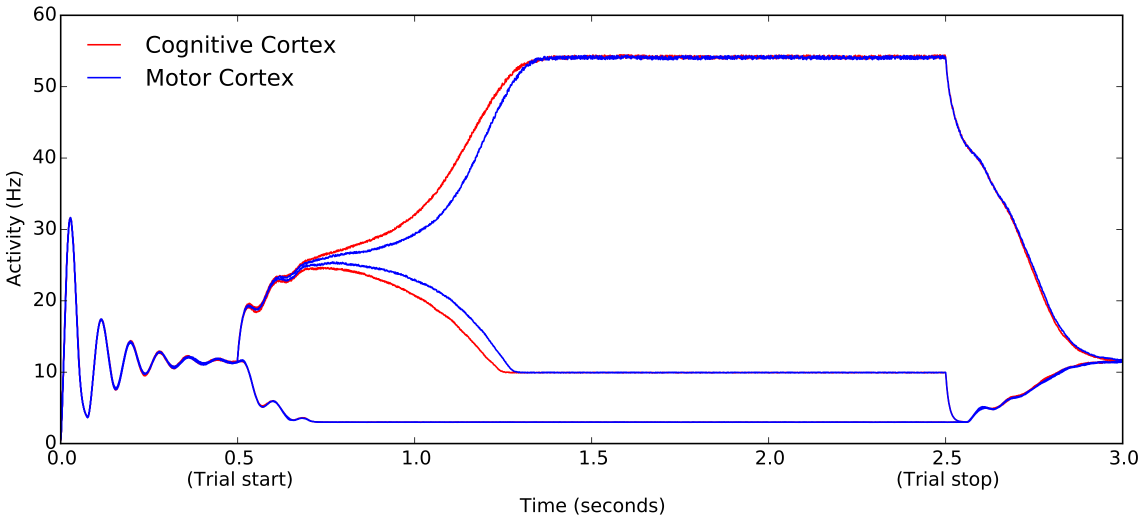

Figure 1. Activity in the cortical population during a single trial of action selection. This is the reproduction of figure 4 of the original article.

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.

Conclusion

We were able to reproduce original results, confirming the correctness of the original implementation of the model.

References

1. M. Guthrie, A. Leblois, A. Garenne, and T. Boraud. "Interaction between cognitive and motor cortico-basal ganglia loops during decision making: a computational study." In: *Journal of Neurophysiology* 109.12 (June 2013), pp. 3025–3040.

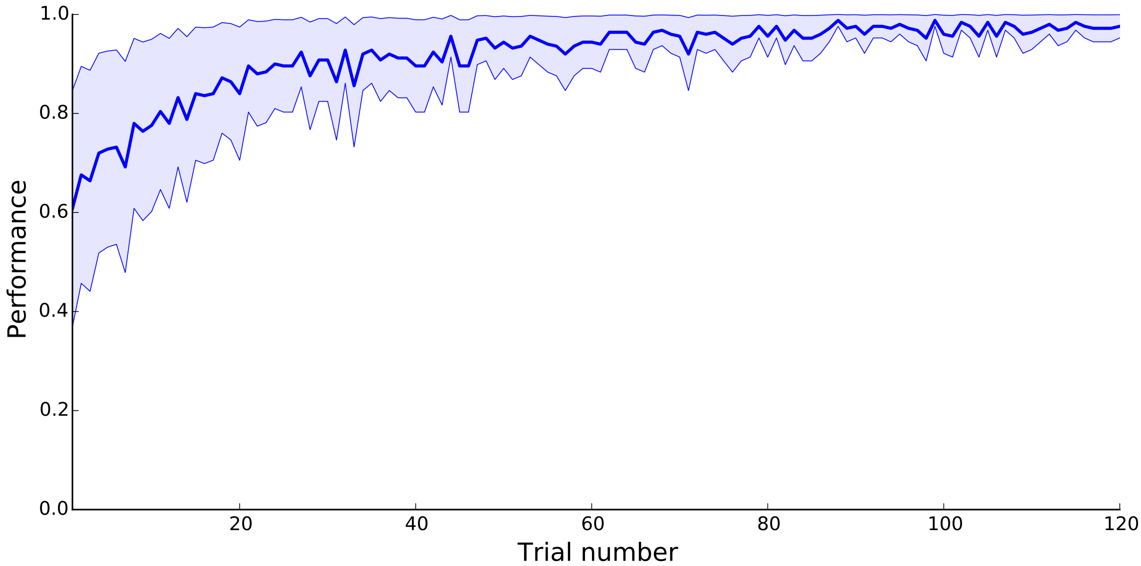

Figure 2. Learning time course over 120 trials, averaged over 250 simulations. The blue filled area indicates the variance of the mean performance.

2. E. Nordlie, M.-O. Gewaltig, and H. E. Plesser. "Towards Reproducible Descriptions of Neuronal Network Models." In: *PLoS Computational Biology* 5.8 (Aug. 2009). Ed. by K. J. Friston, e1000456.