Dynamic and adaptive body schema by learning to predict the sensory consequences of actions

Erik Syniawa[2], Valentin Forch[1] and Fred Hamker

Contact: erik.syniawa@informatik.tu-chemnitz.de

UNIVERSITY OF TECHNOLOGY IN THE EUROPEAN CAPITAL OF CULTURE CHEMNITZ

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Overview

Systems-level approach to develop a body schema and agency:

- The **basal ganglia** will select an action based on the desired state (see Baladron and Hamker, 2020).
- The **central pattern generator** will be execute the action (see Nassour et al., 2020).
- The **cerebellum** will learn to predict the sensory consequences of the motor action in all modalities (vision, touch, proprioception) i.e. the body schema (see Schmid et al., 2019).
- The **prediction error** will be used to improve the prediction and to train action selection in the **basal ganglia**.

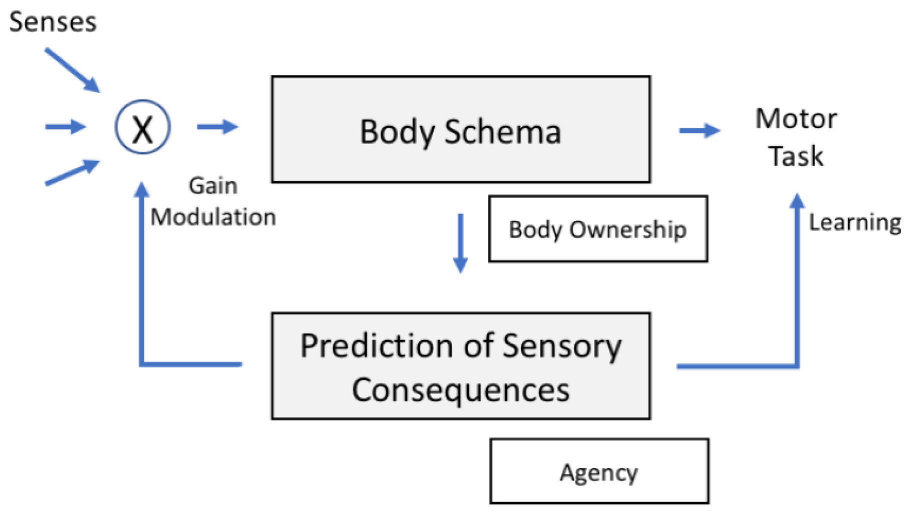


Figure 1: babbas

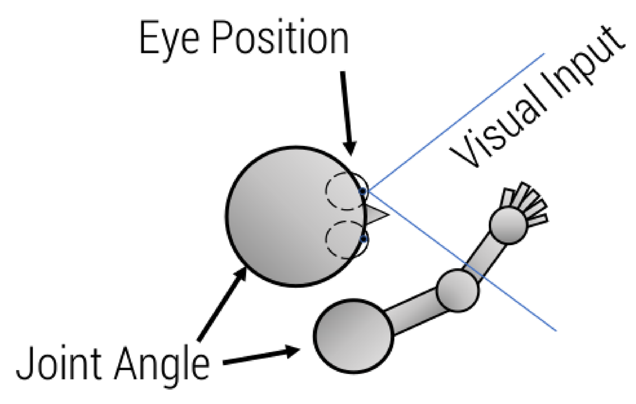


Figure 2: babbas

Sensory Integration[1]

Recurrent Basis Functions (RBF):
RBF have been proposed as a model for multisensory integration and transformation between these frames of reference (Pouget et al., 2002). Figure 2 shows an example where the position of the eyes and a joint are used to predict the position of a stimulus in retinocentric coordinates and vice versa.

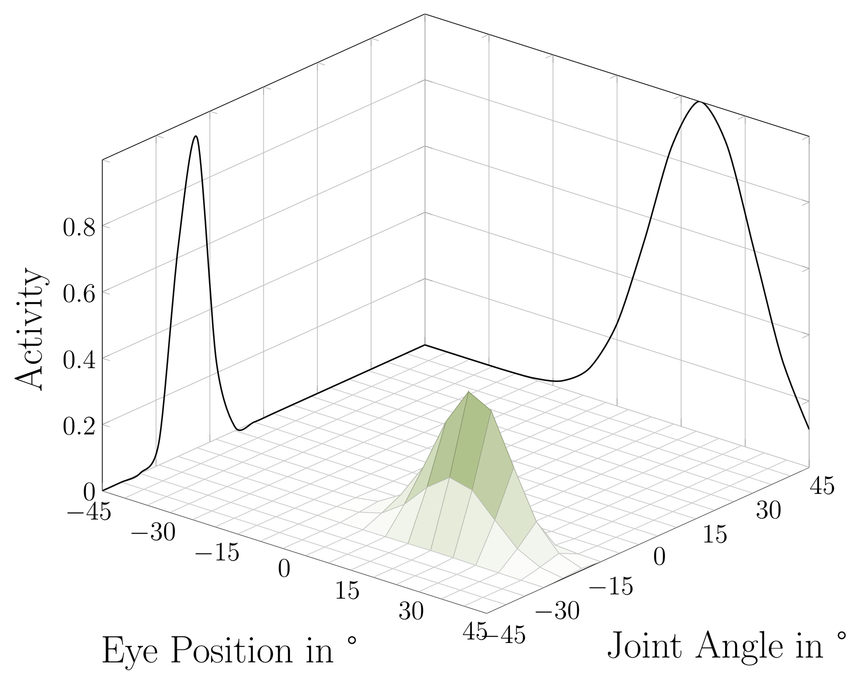


Figure 3: Representation of a RBF population code

Learning a Body Schema[1]

Rate-coded Neural Network:
Our network simulates neural activity in continuous time and is driven by unsupervised (anti-)Hebbian learning (**empty citation**). Excitatory neurons learn to represent the statistical features of their inputs while inhibitory interneurons decorrelate the excitatory responses leading to a sparse neural code.

Neuron Model:

$$\tau^m \frac{dm_j}{dt} + m_j = \sum_j w_{ij} \cdot r_i - \sum_k c_{kj} \cdot r_k$$

$$\tau^\theta \frac{d\theta_j}{dt} + \epsilon \cdot sign(\theta_j) = (r_j - r_{Target})$$

$$r_j = \left[\alpha\left(\frac{2}{1+e^{-\beta(m_j-\theta_j)}} - 1\right)\right]^+$$

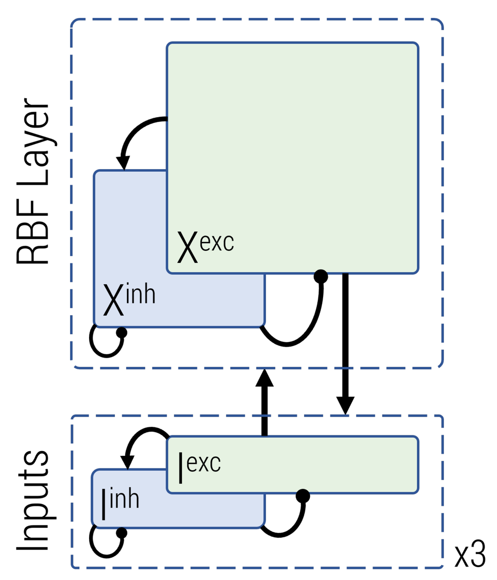


Figure 4: Network Architecture

Synaptic Learning Rules:

Excitatory:

$$\tau^w \frac{dw_{ij}}{dt} = (r_i - \hat{r}_i) \cdot r_j - \alpha_j^w r_j^2 w_{ij}$$

$$\tau^\alpha \frac{d\alpha_j^w}{dt} = \left([r_j - \gamma]^+\right)^2 - \alpha_j^w \text{ with: } w_{ij} = [w_{ij}]^+$$

Inhibitory:

$$\tau^c \frac{dc_{kj}}{dt} = r_k \cdot r_j - \alpha_j^c r_j c_{kj} \text{ with: } c_{kj} = [w_{kj}]^+$$

Results:
RBF-Neurons develop receptive fields (RF) and show shifting gain fields. This behavior is also found in the cortex (Pouget et al., 2002).

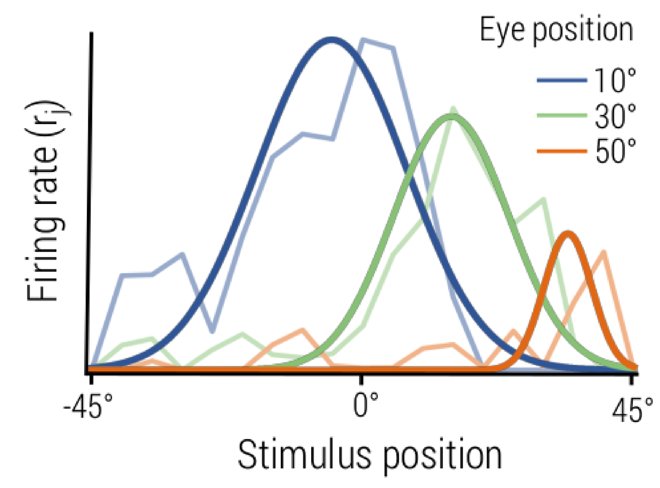


Figure 5: Gain Fields

Basal Ganglia[2]

The 3-factor learning principles are primarily determined by presynaptic and postsynaptic neuron activity, as well as the dopamine signal.
The labels high and low indicate whether the pre- and post-activity is more than or less than a given threshold (for example, mean population activity).

DA+ and DA- labels indicate if SNc activity is above or below a given threshold. A sign specifies the weight changes in the relevant projections for each combination of these criteria (+„ no sign). Table S8 contains the real mathematical explanation of plasticity, in addition to the general description offered.

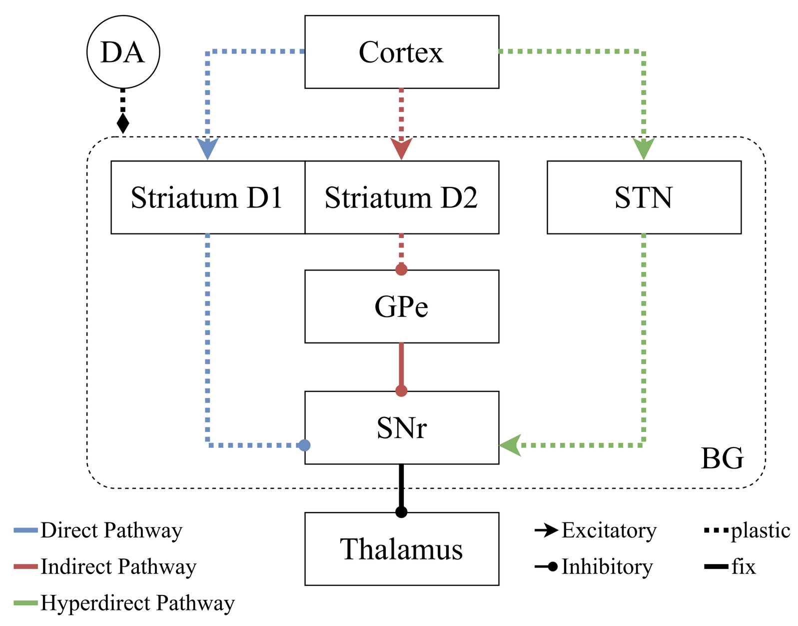
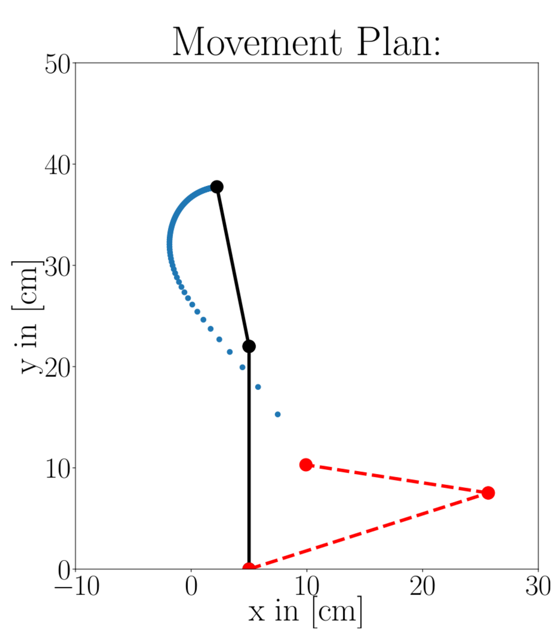


Figure 6: Modeling of segregated basal ganglia pathways

		Dopamine				
		DA +		DA -		
		Post-activity				
		High	Low	High	Low	
Pre-activity	High	+		-		Cortex-D1
	Low	-				
	High	-		+		Cortex-D2
	Low			-		
	High	+		-		Cortex-STN
	Low	-				
	High	-	+		-	D1-SNr
	Low					
	High		-	-	+	D2-GPe
	Low					
	High	+	-		+	STN-SNr
	Low					

Table 1: +: LTP; -: LTD; no sign: no weight change

Motor Learning with the Basal Ganglia[2]



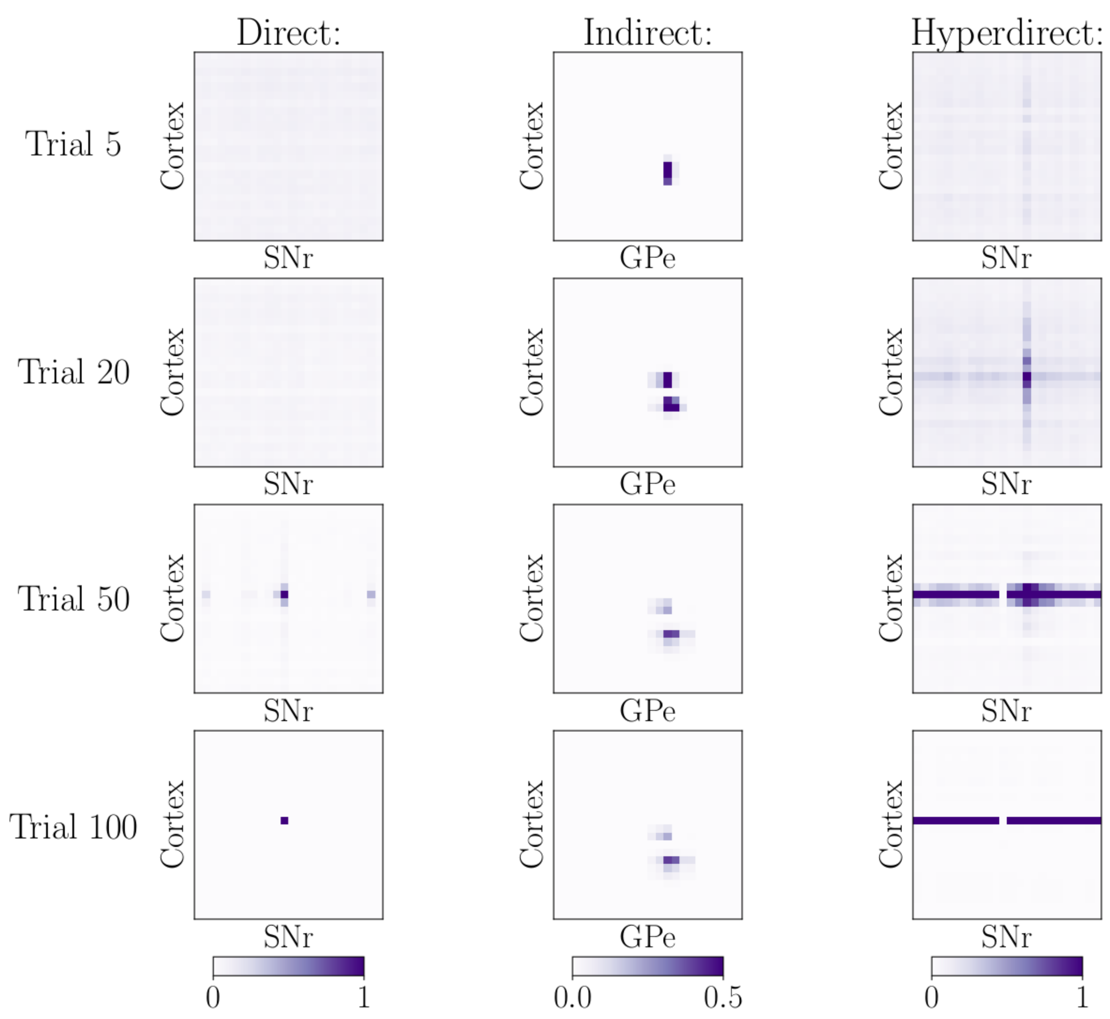


Figure 7: Right: Development of motor learning in the different pathways.

A goal position (**black**) has to be reached from a starting position (red).

This goal informs both, amotor cortex-basalganglia loop and the cerebellum. The motor cortex-basal ganglia loop selects aconcrete action, which determines the parameters of the CPG in the brainstem. Learning occurs when an achieved hand position is novel through dopamine-modulated Hebbian plasticity that reinforces the association between the executed action and the reached hand position.

References

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