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

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The Active Self
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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**.

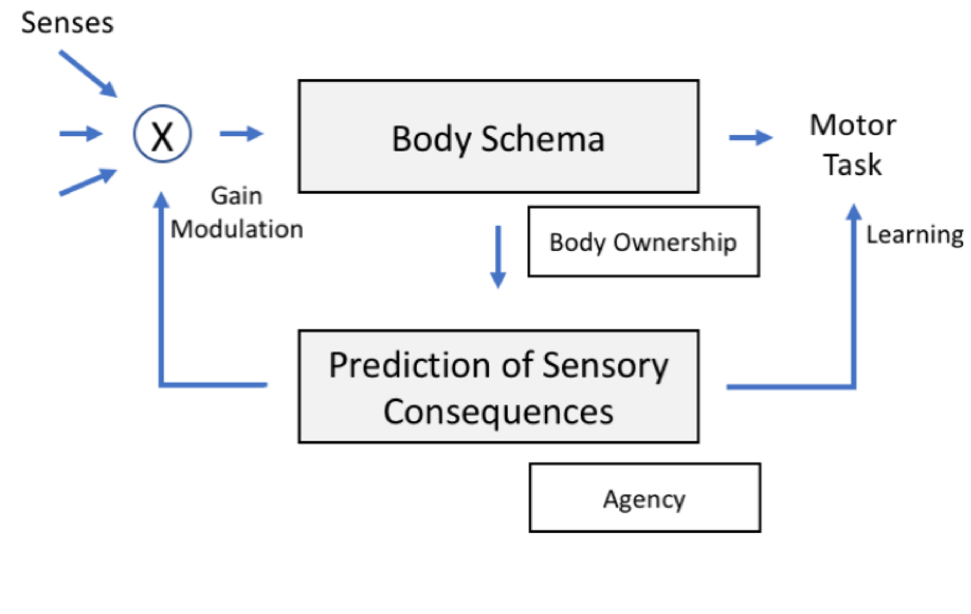

Figure 1: babbas

Setup

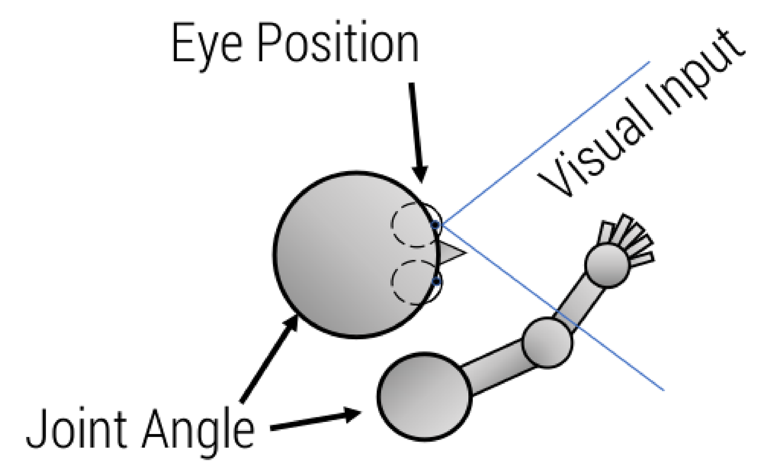

Figure 5: Current virtual robot setup.

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.

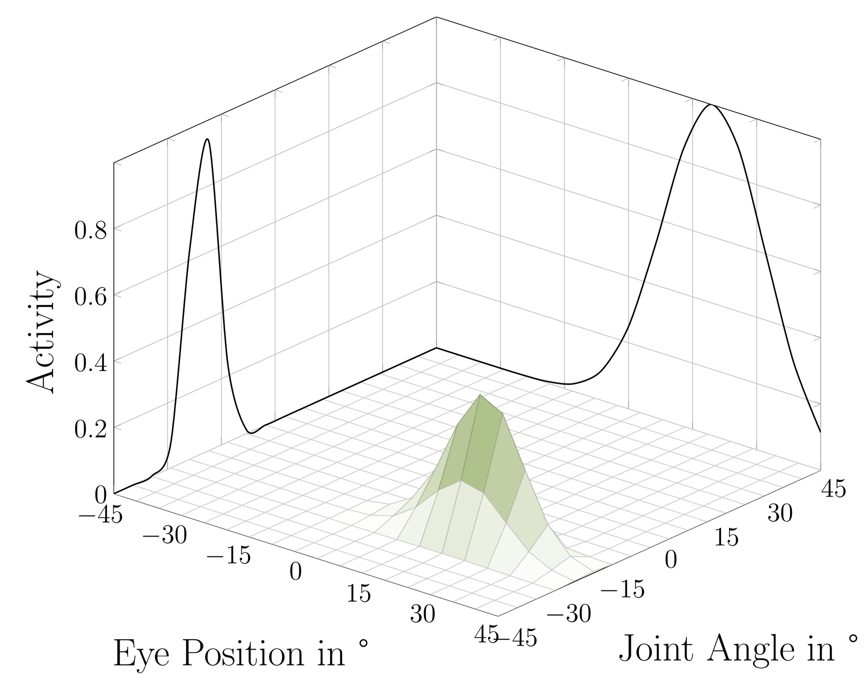

Figure 2: Representation of a RBF population code

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:

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

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

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

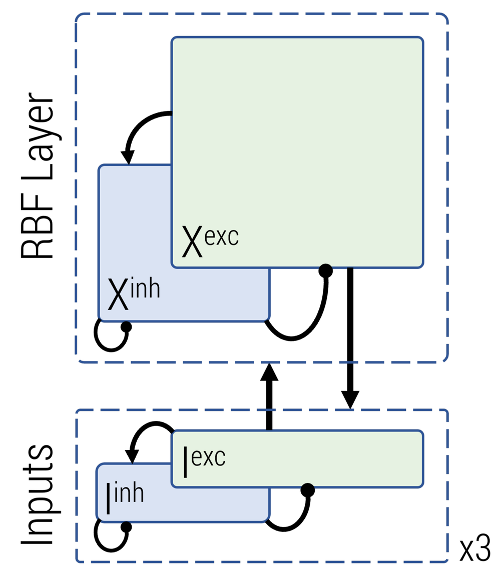

Figure 3: Network Architecture

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:

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

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

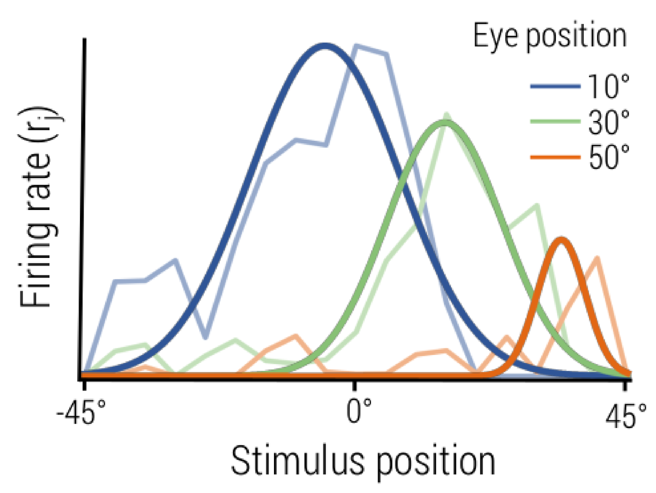

Figure 4: Gain Fields

Basal Ganglia[2]

Network of the Basal Ganglia (BG):

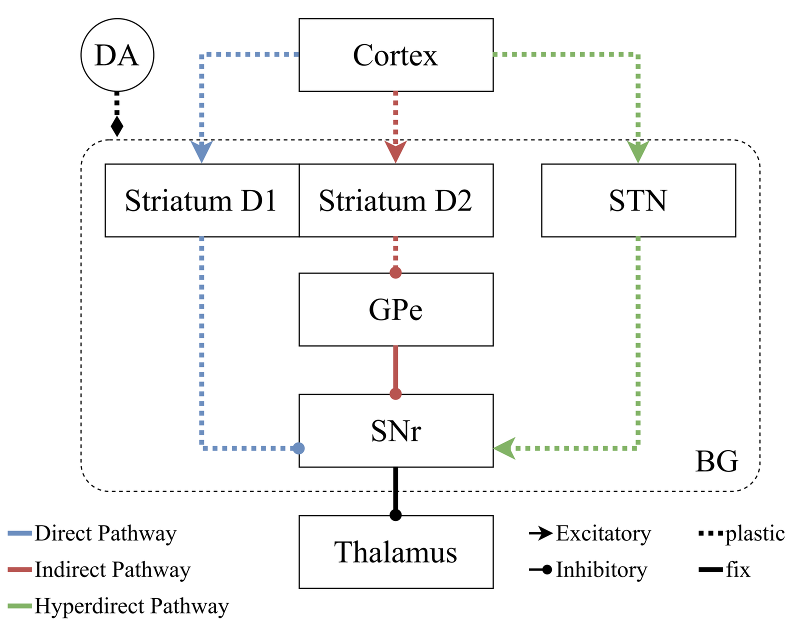

Figure 6: Modeling of segregated basal ganglia pathways

Through dopamine-modulated mechanisms, the BG enable motor category learning (Seger, 2008) and are involved in establishing associations between stimulus and responses (Packard & Knowlton, 2002). Due to the modulating effect of dopamine (DA) on the plasticity of the BG, this model acts as a kind of reinforcement learning agent.

Learning in the different pathways:

The learning principles are primarily determined by presynaptic and postsynaptic activity, as well as the DA-signal (see Table 1). 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 the SNc activity exceeds a given threshold or not. A sign represents the weight changes in the relevant projections for each combination.

		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]

Reaching task:

A goal should be reached in a plane (green). The BG should choose the right movement trajectory (blue) to get from a starting arm position (red) to arm position to reach the goal (**black**). See Figure 7.

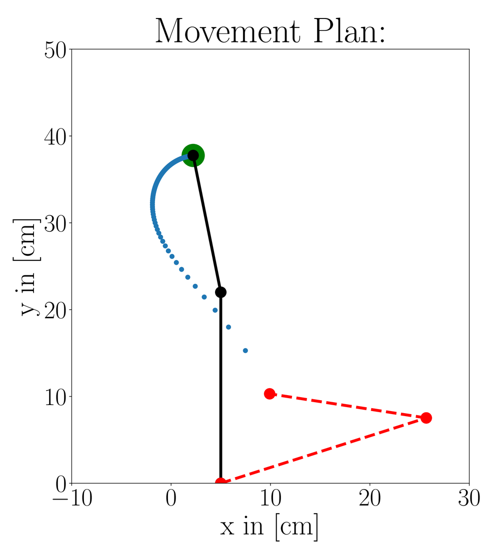

Figure 7

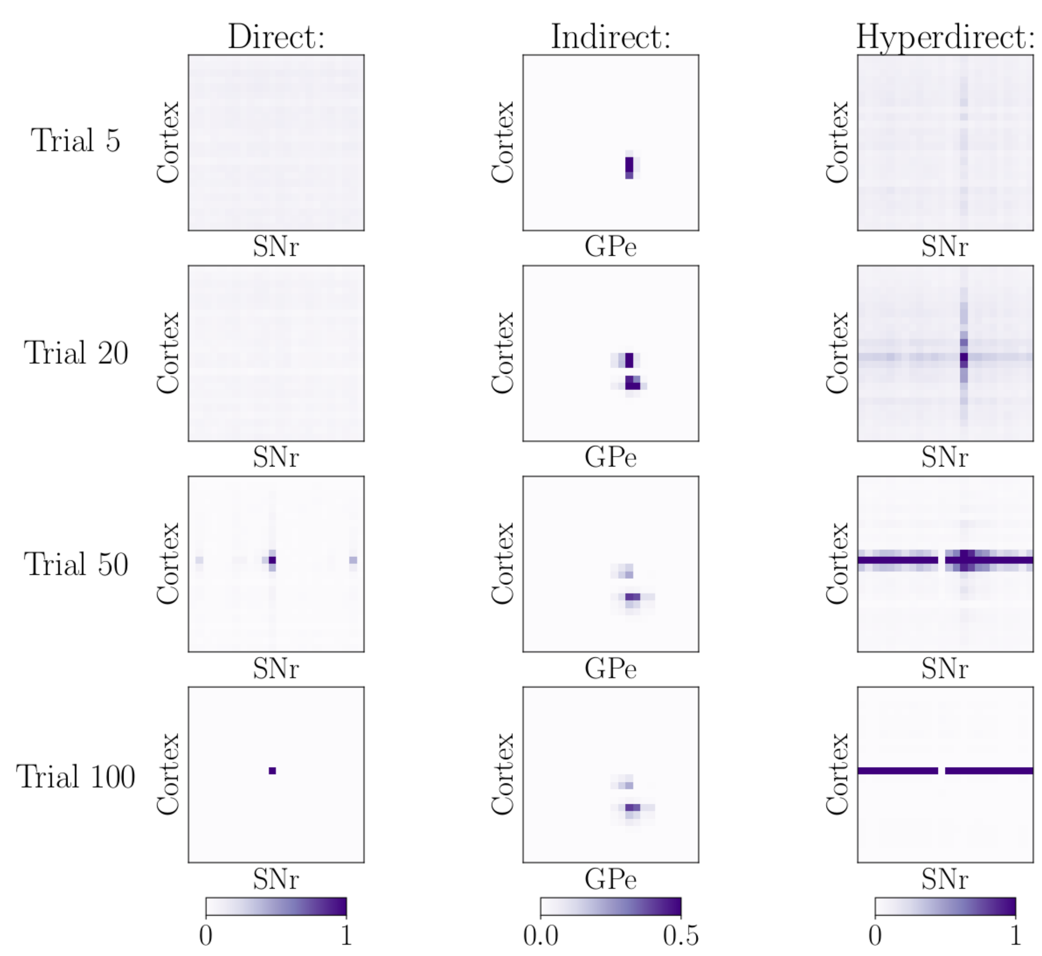

Figure 8

Figure 8 shows the development of the connection strengths in the different paths. At first, unrewarded connections (e.g. movements) are suppressed by the indirect path. Through rewarded selections, a direct and hyperdirect path slowly works its way out. The direct pathway inhibits a neuron associated with rewards in the GPi, while the hyperdirect pathway specifically excites neurons encoding alternative hues in the GPi. This influences the activity of the thalamus so that only one neuron becomes active.

References

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