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

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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**.

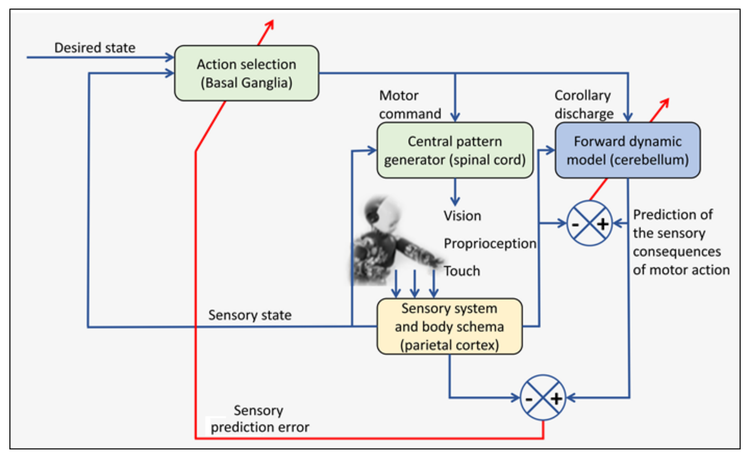



**Figure 1:** babbas

## Recurrent Basis Functions[1]

Hier was zu dieser Veröffentlichung Pouget et al., 2002.

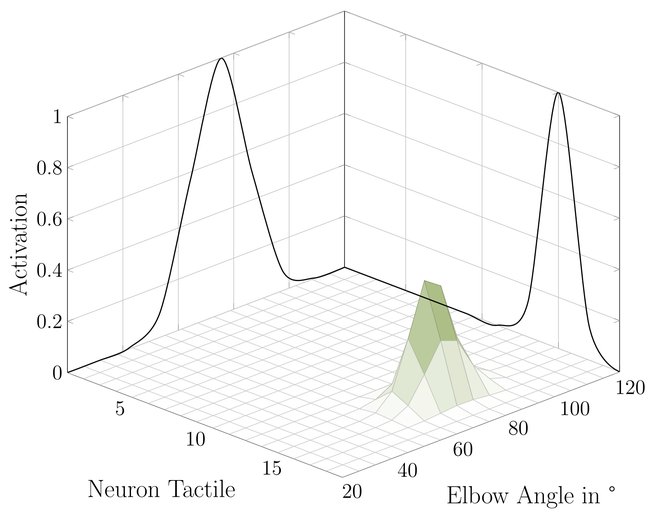



**Figure 2:** babbas

## Learning a Body Schema[1]

## 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.

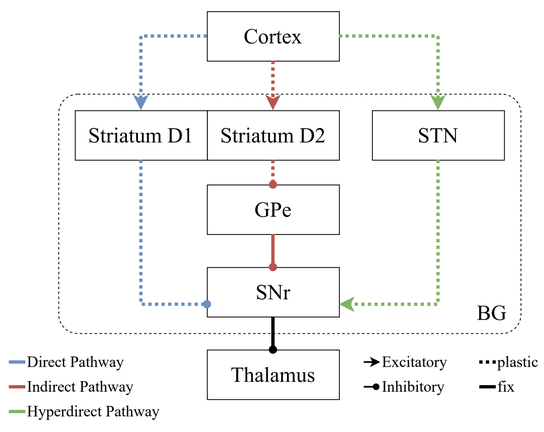



**Figure 3:** Modeling of segregated basal ganglia pathways

| | | 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]

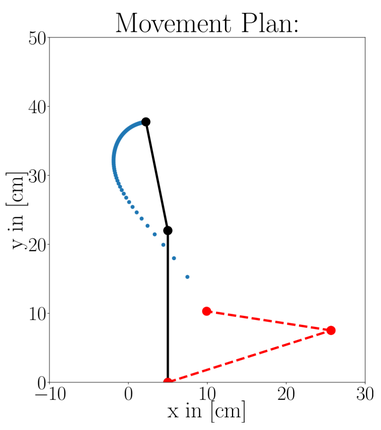
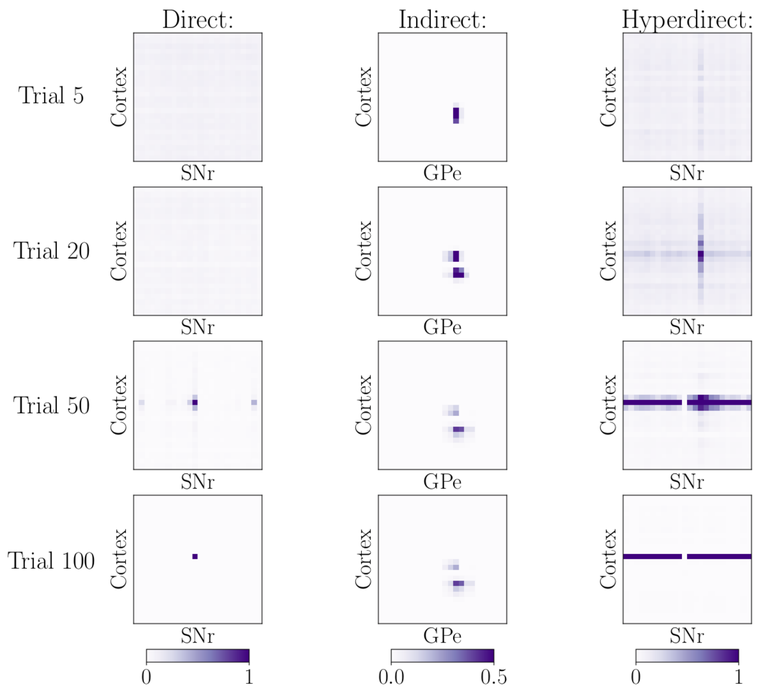



**Figure 4:** Right: Development of motor learning in the different pathways.

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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.

## References

Baladron, J., & Hamker, F. H. (2020). Habit learning in hierarchical cortex–basal ganglia loops. *European Journal of Neuroscience*, *52*(12), 4613–4638. https://doi.org/10.1111/ejn.14730

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