Human Brain Project

Learning Techniques for Neurorobotics - A Survey on the Role of the Factor Time

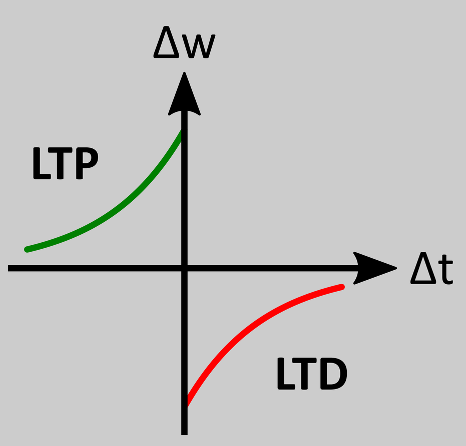
Neurorobotics enables the interaction of simulated biological neural networks with both virtual and real environments in closed perception-action loops. Controlling robotic actuators, processing sensor readings and implementing goal-directed behavior requires the adjustment of synaptic weights by means of learning. The temporal dynamics of the detailed neural models employed in neurorobotics enable the use of learning techniques which incorporate a notion of time. This poster provides an overview of concepts and methods from this field with a special focus on prospective applications in neurorobotics.

SINGLE NEURONS

Short-Term Plasticity (STP)

STP models temporary short-term facilitation and depression of synaptic efficacies caused by sustained spiking activity. In the absence of spikes, the synapse recovers within a few hundred milliseconds, a timescale relevant in tasks like motor control (Tsodyks et al., 2013).

Spike-Timing-Dependent Plasticity (STDP)



STDP (e.g. Bi et al., 2001) is a theoretical model for the experimentally observed change of synaptic weights based on the relative timing Δt between presynaptic and postsynaptic spikes. If a presynaptic spike precedes a postsynaptic one the synaptic weight is increased, which is referred to as Long-Term Potentiation (LTP). Analogously, anticausal spike pairs yield Long-Term Depression (LTD). Variations of this concept rely on different learning windows or use spike triplets instead of pairs. STDP enables the learning of temporal spike correlations.

Reward-Modulated STDP (R-STDP)

STDP operates on the timescale of milliseconds. To incorporate external feedback with delays in the order of seconds, R-STDP (e.g. Legenstein et al., 2008) stores a trace of potential weight updates in a synaptic tag. An external reward modulates the trace and triggers the actual weight update.

Body Map Development

Using robotics tools, Yamada et al. (2013) demonstrated the formation of body maps by connecting a fetus simulation to a spiking neural network model of the nervous system.

Operant Conditioning

Cyr et al. (2014) combined STP and STDP to develop a simple minimal neural component for operant conditioning in neurorobotics.

Learning of Visual Features

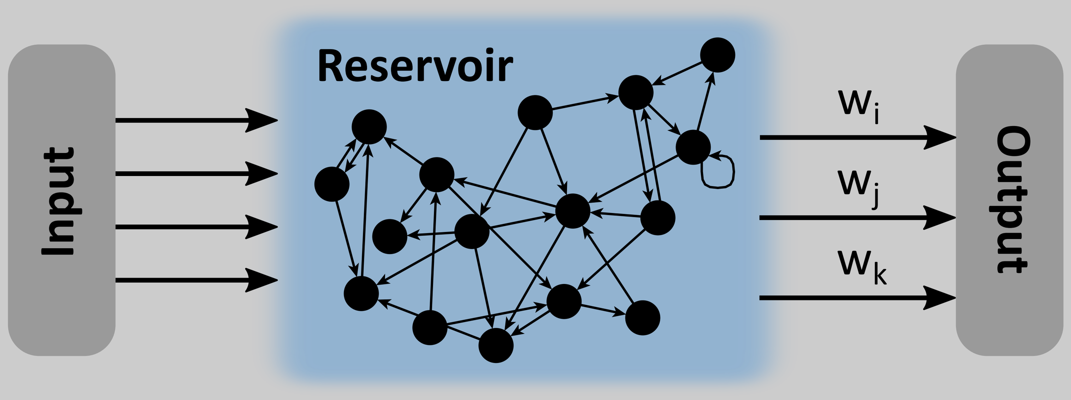
Masquelier et al. (2007) presented a neural network for learning of visual features through STDP.

The relative timing of spikes and rewards can determine synaptic weight updates

RECURRENT NEURAL NETWORKS

Reservoir Computing

Reservoir computing techniques (e.g. Jaeger et al., 2009) leverage the temporal dynamics of recurrent neural networks for computation. Different methods based on analog neurons (Echo State Networks) and spiking neurons (Liquid State Machines) were conceived independently by Jaeger (2001) and Maass et al. (2002). The reservoir, a recurrent neural network with fixed synaptic weights, is generated randomly and projects the input into a high-dimensional feature space. Dedicated linear readout units with trainable weights map the reservoir state into the output space. Learning requires adapting only these output weights and is therefore considerably simpler compared to computing weight updates for the complete network.



Associative Memory

Hopfield nets (Hopfield, 1982) implement associative memory based on the attractor dynamics of a recurrent neural network topology. Jaeger (2014) introduced conceptors for storing different dynamical patterns in a single reservoir. With an extension called autoconceptors, these patterns can be accessed by presenting a cue of the desired output.

Storing Human Motion Patterns

Jaeger (2014) used conceptors to store human motion patterns which where retrieved using motion capturing. In a second step, these patterns were re-generated and visualized. Linear blending between conceptors enabled smooth transitions between successive patterns.

Morphological Computation

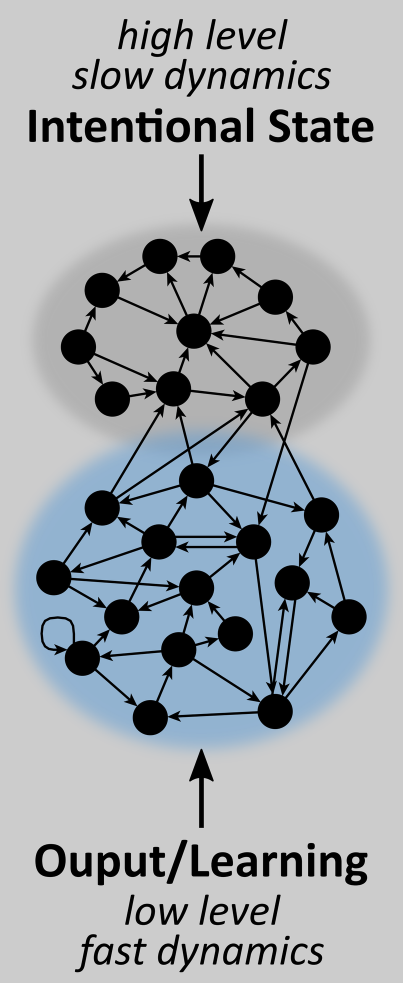
Depending on the morphology of a robot, the reservoir can be replaced by its physical body dynamics. In a theoretical study, Nakajima et al. (2013) emulated nonlinear dynamics with a soft octopus arm model.

The temporal dynamics of recurrent neural networks can store and process information

NEURAL NETWORK HIERARCHIES

Multiple Timescales Recurrent Neural Networks (MTRNNs)

MTRNNs (Tani, 2014) are hierarchically organized neural networks which are composed of several recurrent neural networks with parametric biases (RNNPBs). They encompass two directions of information processing. A top-down pathway predicts perceptual and internal states based on an intentional state which is provided as one of the inputs. Learning is performed bottom-up and driven by the actual perceptions. Each RNNPB runs at an own timescale with slower dynamics corresponding to higher levels of abstraction. By setting the prediciton of a higher level as intentional state of the lower, the slow high-level dynamics provide context to the lower control levels.



Hierarchical Temporal Memory (HTM)

The HTM algorithms conceived by Hawkins et al. (2011) model layer 3 of neocortical brain regions at a very abstract level. A spatial pooler maps input to sparse distributed representations. Future input is predicted by a temporal pooler. Since the predictions change slower than the input, the output becomes more stable and changes on a slower timescale in higher regions.

MTRNNs for Neurorobotics

Tani (2014) applied MTRNNs in a neurorobotics experiment with a humanoid robot. He demonstrated how basic action primitives were learnt by the fast low-level subnetwork while the high-level subnetwork with slow dynamics only stored abstract action sequences.

Consequences for Neurorobotics

Since relative timing can encode relevant contextual knowledge, it is crucial in neurorobotics to ensure that the speed of the neural network simulation matches the timescale of the robot dynamics.

Different timescales in network hierarchies enable learning at different levels of abstraction

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