

Poster presentation

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Spike-based reinforcement learning of navigation

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Introduction

We have studied a spiking, reinforcement learning model derived from reward maximization [1,2] where causal relations between pre- and postsynaptic activity set a synaptic eligibility trace [2,3]. Neurons are modeled according to the "Integrate-and-Fire" model with escape noise. Synapses are binary and are modulated via the release probability. The synaptic release probability is updated when a global reward signal (such as dopamine) is received.

We have used the learning algorithm in a model of the Morris Water Maze task. The simulated rat explores the environment in random search. After only few trials the rat has learned to approach the goal from arbitrary start conditions, see Figure 1. The model features automatic generalization in state and action space due to coding by overlapping profiles of place cell and action cells [4].

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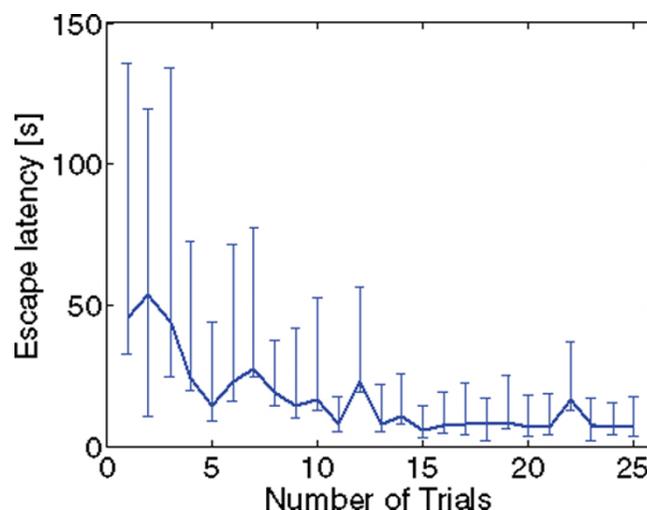


Figure 1
Escape latency versus number of trials. Escape latency measures the time it takes the simulated rat to reach a hidden platform starting from arbitrary initial conditions. Learning is achieved in less than 20 trials. Error bars indicate 25% and 75% percentiles.