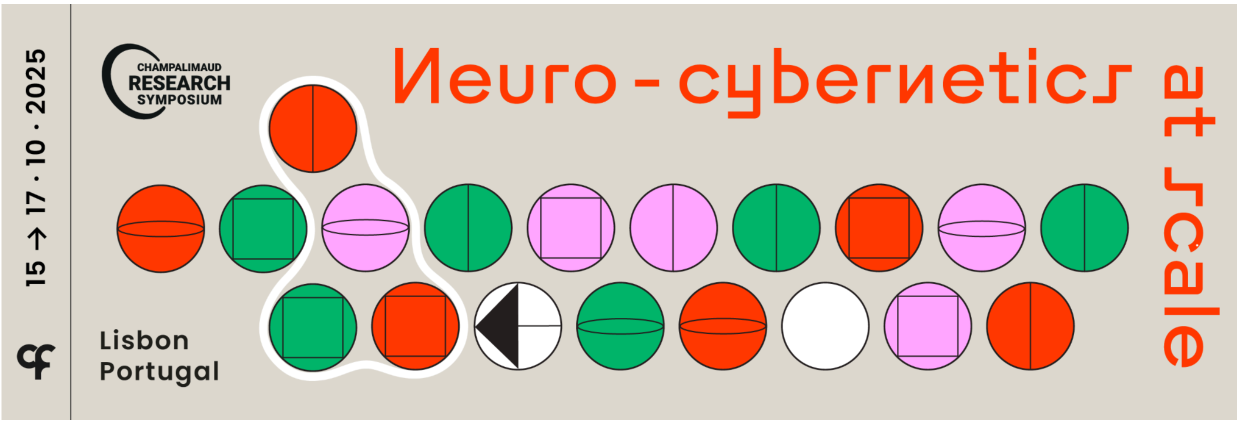


# A Bio-Inspired Algorithm Enables Scalable Training of Spiking Neural Networks Using Feedback Control Across Layers

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Unlike artificial networks, biological neural networks communicate via spikes and learn with local plasticity, allowing scalable credit assignment through feedforward and feedback signals [1, 2]. However, existing bio-plausible learning rules can only train shallow Spiking Neural Networks (SNNs), which reduces their ability to accurately model how biological systems learn. This also limits their effectiveness for on-device training using neuromorphic hardware, which mimics key brain features like spike-based communication and limited energy availability [3,4].

To address this, we introduce a learning algorithm for SNNs that leverages feedback control to compute weight updates locally in space and time [5,6]. Our framework uses spiking control neurons to guide network activity towards a desired target by sending top-down feedback signals into the apical compartment of every neuron and updating weights to minimize this feedback signal over training. This enables supervised learning across multiple layers, while being fully compatible with the constraints of biological and neuromorphic systems.

We evaluate our algorithm by training SNNs on a mixed-signal neuromorphic device, the DYNAP-SE [7], across various classification tasks. We achieve the expected test-time accuracy, with results that are consistent with simulations both quantitatively and qualitatively.

Our results thus demonstrate bio-inspired, real-time training of multi-layer SNNs on specialized neuromorphic hardware, paving the way for next generation AI. Strikingly, the competitive performance of our algorithm shows that learning by minimizing feedback control can scale effectively, even under constraints similar to those found in the brain, such as substrate variability, spike-based communication, and imprecise synaptic weights.

**feedback control, neuromorphic computing, bio-inspired learning, spiking neural networks, on-device training**