A biologically plausible recurrent spiking architecture for modeling nonlinear dynamic mechanical systems

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Spiking Neural Networks (SNNs) have gained significant attention in recent years because their spike-based, event-driven communication, together with the inherent sparsity of spikes, is believed to enable highly energy-efficient computation. This property has been effectively leveraged in a variety of classification and regression tasks. Although inspired by biological neural systems, most existing SNNs bear only limited resemblance to their biological counterparts in terms of dynamics and learning mechanisms. Several studies have aimed to better understand the mathematical functioning of the brain to incorporate greater biological plausibility into existing neuron models. One such approach is to train the networks using a more biologically plausible learning rule called eligibility propagation (e-prop), which serves as an alternative to conventional Back Propagation Through Time (BPTT). In this study, we train a recurrent-SNN composed of Adaptive-threshold based Leaky Integrate-and-Fire (ALIF) neurons using the e-prop learning rule on datasets derived from viscoelastic rheological models. We establish an analogy between these rheological models and the membrane dynamics of LIF neurons, highlighting their mathematical similarity and providing a physical justification for employing SNNs in mechanics beyond energy-efficiency considerations. To model geometrically and physically nonlinear structural deformations, we further propose a multi-layer recurrent spiking architecture that integrates Legendre Memory Units with ALIF neurons for predicting nonlinear transient displacement responses of plates obtained from shock tube experiments. To train this architecture, a hybrid learning approach is introduced by combining e-prop and BPTT. Finally, a comparative analysis between e-prop and BPTT is conducted, emphasizing their respective trade-offs in accuracy, convergence speed, and computational efficiency.