More than Spikes: Neurons as Dynamical Systems for Intracellular Processing

Introduction Traditional computing systems utilize the computational primitive of Boolean logic, operations on a population of bits, and a synchronous operating clock, to enable logical and symbolic operations. Largely influenced by analogy to this approach, recent developments in neuromorphic computing have focused on the action potential, or spike, as the fundamental unit of neurally inspired computing. This has led to a focus on population-level encoding approaches, in which simplified units such as the leaky-integrate-and-fire (LIF) are utilized as universal function approximators, and largely implements 'spiking equivalents' of traditional computer algorithms [1], at the cost of requiring thousands of units and hand-engineered algorithms. In contrast, biological neurons are nonlinear units, with a plethora of intracellular dynamics which directly operate on inputs, rather than relying solely on population-level representations. *We argue that these intracellular dynamics, which perform specific computational operations rather than a generalized logic, are the computational primitives of neural systems.*

Neurons Process by Intracellular Dynamics The primary difference between artificial neural networks (ANNs) and biological systems is the presence of spatiotemporal dynamics, which range order of magnitude in both temporal and spatial scales, compared to ANNs which primarily utilize instantaneous activation functions. These dynamics allow intracellular processing by integrating inputs at different time-constants and allowing mixtures of these signals. Even the simplest dynamics, such as a continuously evolving internal state, allows computations such as integrals and correct assignment of error through time [2]. Utilizing even such simple dynamics in a recurrently connected system can lead to complex but predictable population-level dynamics that can act as function generators for a variety of tasks [3]. When further expanded from a first-order to second-order differential equation, internal dynamics are able to implement history-dependent effects such as rebound spiking, which has been shown as essential for maintenance of information over extended periods of time [4], and implicated as a mechanism for working memory [5]. Further allowing for spatial compartmentalization of membrane dynamics allows otherwise complex operations such as division and multiplication to occur within the arborization of a single neuron [6]. Collections of dendrites are then able to implement complex operations such as context-dependent processing [7], sensory fusion in neocortex [8], and continual learning on multiple tasks in hippocampus [9]. Local processing of inputs may allow an implicit reconstruction and operation on presynaptic membrane potential, circumventing information bottlenecks otherwise imposed by binary spikes [10].

Intracellular Dynamics Modify Intercellular Processing While simple LIF-like units respond with monotonically increased firing rate in response to input spikes, additional intracellular dynamics enable the modulation of intercellular spike-based communication. For example, units with a controllable inter-spike-interval pattern, which requires at least fourth-order differential equations, carry higher information density than firing rates alone [11]. This increased information density can allow for multiplexing of multiple streams of information [12], which then supports supervised [13], unsupervised [14], and one-shot [15] learning. Local populations of neurons can also become synchronized due to small-magnitude oscillations in local-field potentials coupling with intracellular responses, which then have causal effects on intracellular communication, by suppressing or increasing intracellular responses to incoming spikes. Oscillations of various frequencies and underlying physical origin have been implicated in multiple computational roles, including gating of information, spatial attention in visual systems [16], role-binding [17], and working memory in prefrontal cortex [18], and prevents catastrophic interference in hippocampus [19].

Training In recent years, LIF-like units have been successfully trained using backpropagation methods, similar to those in standard deep-learning approaches [20]. However, such approaches fail to optimize systems which require multiple temporal scales of interactions, as will be the case in systems which utilize intracellular and intercellular processing. Therefore, to train such systems, we will need to integrate biological learning rules which operate over multiple temporal scales, along with recent advances in dynamic systems approaches [21], [22] which fit dynamics of systems rather than function approximations, akin to physics-informed neural networks.

Implications for Analog Design and Scaling While the number of candidate dynamics outlined above prohibits bio-mimicry approaches, the intracellular behaviors outlined above are all second-order equations, suggesting that neuromorphic systems implement neural units as a mixture of universal-oscillators. Combined with negative feedback mechanisms, this class can create stable attractors and other behaviors that mitigate the intrinsic noise and variability of analog systems. Simultaneously, utilizing locally complex and dense computation within individual neurons can minimize the number of intercellular connections that typically accompanies population encoding. This effect can be compounded by imposing general topological and functional motifs that emphasize local communication [23], resulting in a hierarchy of extremely dense intracellular analog interactions, locally analog but mean-field oscillatory interactions, and long-range interactions via spiking activity only. Such minimization of long-range communication is critical for allowing high throughput of flexible digital routing [24], and enables relatively seamless interaction with HPC-based systems for scaling.

Necessary Datasets To continue to develop a comprehensive view of the interaction of spike-based and intracellular dynamics, we must continue to collect datasets which record both behaviors. Recently, systems neuroscience has emphasized methods which enable recording of large populations of neural spikes, but which do not record intracellular dynamics provided by earlier methods. However, novel and emerging techniques have allowed for recording of large populations, while also providing information on the intracellular responses of dendritic arborizations [25], including neurotransmitter specific responses [26], and relating these responses to systems-level activity [27].

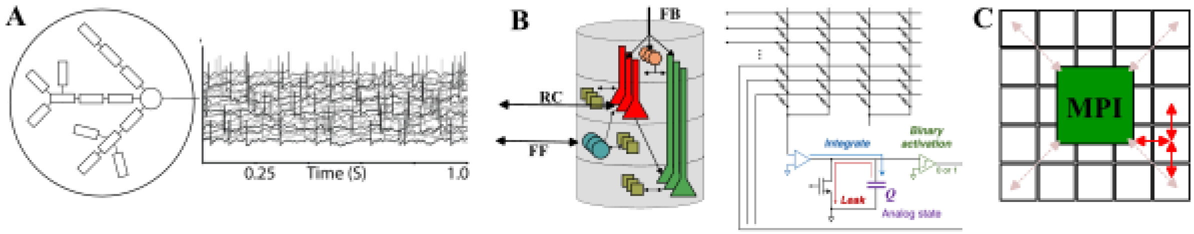

Fig. 1. A multi-scale approach to processing. **A** An individual neuron is made of multiple analog compartments, each of which has a unique combination of dynamics, chosen dependent on the use-case. **B** Local cortical structures, which are highly interconnected and transmit analog and spike values locally. Such a population could be manufactured into a single chip. **C** For larger scale systems, individual analog chips (from B) communicate to other distance chips only by spikes. These spikes can be routed by microprocessors (eg: MPI), allowing integration into existing HPC architectures.

SNL is managed and operated by NTESS under DOE NNSA contract DE-NA0003525

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