Nanoscale neuromorphic networks and criticality: a perspective

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Keywords: criticality, dynamical systems, neuromorphic networks, abiotic criticality, avalanche dynamics, memristive devices, atomic switch

Abstract
Numerous studies suggest critical dynamics may play a role in information processing and task performance in biological systems. However, studying critical dynamics in these systems can be challenging due to many confounding biological variables that limit access to the physical processes underpinning critical dynamics. Here we offer a perspective on the use of abiotic, neuromorphic nanowire networks as a means to investigate critical dynamics in complex adaptive systems. Neuromorphic nanowire networks are composed of metallic nanowires and possess metal-insulator-metal junctions. These networks self-assemble into a highly interconnected, variable-density structure and exhibit nonlinear electrical switching properties and information processing capabilities. We highlight key dynamical characteristics observed in neuromorphic nanowire networks, including persistent fluctuations in conductivity with power law distributions, hysteresis, chaotic attractor dynamics, and avalanche criticality. We posit that neuromorphic nanowire networks can function effectively as tunable abiotic physical systems for studying critical dynamics and leveraging criticality for computation.

1. Background

1.1. Criticality in nature
Nature is awash with complex systems that exhibit behavior which collectively extends beyond the predicted behavior of the system’s individual components [1–3]. This is an example of emergent behavior, or properties which cannot be predicted by extrapolation from a system’s individual components alone. Rather, the system’s state evolves through the interactions of its components [4, 5]. Numerous studies have devoted considerable effort to elucidating the mechanisms underlying such complex dynamical systems [3, 6–8]. One potential mechanism that has emerged as a candidate for describing complex behavior is criticality. The concept of criticality refers to a system poised at the point between ordered and disordered states (a ‘critical point’), analogous to a phase transition [9]. Such systems exhibit long-range spatio-temporal interactions over many scales [9]. Scale-invariant phenomena can be represented in the form of power-law (Pareto) probability distributions, \( f(x) \propto x^{-\beta} \), where \( \beta \) is a positive real number [10–13]. Furthermore, the tuning of some parameter that controls or governs the system (e.g. temperature, strain)—whether driven by the system intrinsically or by an external agent—can direct the system away from the critical point and into sub- or supercritical regimes [9, 14–17]. In addition, it has been suggested that a system operates optimally when poised at its critical state [9, 18–20].
In nature, numerous abiotic and biotic systems are suspected to exhibit critical dynamics. Evidence of power-law distributions in abiotic phenomena include the dynamics of arrays of magnetic dipoles, cellular automata, earthquake size and frequency, forest fire propagation, atmospheric flows, climate fluctuations, word frequency, wealth distribution, economic systems, and solar flares [14, 15, 21–28]. Similarly, power-law distributions are observed in a variety of biotic phenomena including evolutionary ecology, gene networks, morphology, animal collective movement (e.g. flocks of birds), mitochondrial networks in the heart, and neural systems, among others [13, 29–39].

1.2. Criteria for criticality

The use of power laws as the sole criterion for determining whether a system demonstrates criticality has been challenged previously [40, 41]. The criteria for determining whether or not a system demonstrates criticality are sometimes misunderstood or loosely applied. In certain fields, studies have been published professing that a system exhibits critical or self-organized critical dynamics based solely on the exhibition of a power-law distribution. Such work sometimes overlooks non-critical phenomena that are capable of producing power-law distributions. Prominent examples include successive fractionation, multiplicative noise, randomly-terminated exponential processes, preferential attachment, and the typing of random words [42–46]. Therefore, power-law relationships alone are insufficient to conclusively demonstrate that a system is critical.

Criticisms of criticality necessitated the establishment of specific criteria to define a critical system. Physicists and neuroscientists have contributed significantly to this effort by developing a robust set of criteria that critical systems should meet, including:

(a) Power-law relationships, \( p(x) \propto x^{-\beta} \), between order parameter, control parameter and size of system.

(b) Finite size scaling of correlation length and order parameter susceptibility (i.e. distribution cut-offs diverge with system size).

(c) Mathematical relationships between power-law exponents for different parameters in a dynamical system [42, 47].

(d) Evidence of shape (data) collapse: multiple phenomena or events across different scales exhibiting self-similarity (e.g. event duration) [47].

(e) Tunability: the ability of a system state to be regulated by a control parameter that drives the system into sub- or supercritical regimes, resulting in non-critical dynamics [42].

These requirements, among others, for critical systems have provided focus for experimental tests of criticality in a variety of systems [42].

1.3. Criticality in neuronal systems

Few potentially critical biological systems have received more attention than the brain’s cortical neuronal system. Experimental and theoretical studies over the last few decades provide support for the argument that the brain demonstrates critical dynamics [10, 39, 42, 48, 49]. Studies of in vitro neurons and cortical tissue slices have demonstrated statistically robust power-law distributions in neuronal spiking events, called ‘avalanches’, in both duration and size of the event [10, 39, 42, 48, 49]. After re-scaling avalanche size and duration, the resulting distributions exhibit a shape collapse, where avalanches of different durations converge onto a universal scaling function [47]. Additionally, in vivo functional magnetic resonance imaging studies of the human brain provide evidence that the brain may exhibit critical dynamics [50, 51]. Computational modeling data from one such study reasonably predicted the patterns of activity in specific regions of the brain when it is in or near a critical state [48]. Other studies showed how critical dynamics were lost in abnormal neural conditions, such as epileptic seizures, in rats and humans [52–54].

Several studies provide evidence that the brain’s performance in operations such as information storage and transmission is optimal when the brain is at or near a critical point [51, 55–60]. However, studying the brain for evidence of criticality as a mechanism for its information processing prowess is an inherently challenging task. Our perspective is that an abiotic system that demonstrates both information processing capabilities and diverse nonlinear dynamics could provide new insights into critical systems. The utilization of a tunable abiotic system would also allow for control over available parameter space, material composition, and network topology, as well as more extensive measurement and analysis methodologies. In our view, neuromorphic networks are a suitable system for advancing the understanding of critical dynamics in neuronal and other biological systems.
2. Nanoscale neuromorphic networks

2.1. General characteristics of physical neuromorphic networks

The first synthetic, brain-inspired computer, the perceptron, was developed in 1958 by Frank Rosenblatt at Cornell University and the United States Office of Naval Research [61]. The perceptron was conceived in an attempt to mimic biological information processing systems and perform difficult tasks such as image recognition [61, 62]. Although this technology failed to achieve the task in its era, the notion of brain-inspired computational systems endured. In 1990, Carver Mead introduced the concept of neuromorphic engineering to describe systems specifically engineered to mimic features of the brain, including co-localized processing and memory [63–65]. Since then, many neuromorphic computational systems have been developed, including atomic switch networks [65–84].

Atomic switch networks are biologically-inspired, abiotic, physical systems composed of highly interconnected networks of nanoionic devices called ‘atomic switches’ [66]. Atomic switches are functionally akin to information-retaining nonlinear circuit elements which exhibit memory-resistive (memristive) switching and quantized conductance in addition to short- and long-term memory elements [66]. Such memristive circuit elements retain information, or memory, of their previous states. Memristive switching is achieved via the formation or degradation of nanometer-scale conductive filaments between structural elements, which arise from voltage- or current-driven ionic migration and reduction/oxidation processes [85]. The memory effect is governed by the size of the formed filament [67]. The ability to tune the conductance of a memristive (atomic) switch via filament formation/degradation is considered analogous to the adaptive strength of synaptic connections between neurons [67], making them an inorganic synaptic analog. Memristive (atomic) switches, functioning as conductance-based inorganic synapses, can form from nanoscale structures that self-assemble into complex networks [68–70]. Various combinations of conductive and insulating materials can be used to produce these networks, including silver, polyvinylpyrrolidone (PVP), sulfur, iodine, and selenide, among others [69–78]. Memristive switch networks of nanoparticles or nanowires, as shown in figures 1(A)–(C), previously demonstrated emergent behavior that isolated atomic switches do not, including spatially distributed memory and recurrent dynamics [70, 79].

Figure 1. Network morphology and power-law distributions in silver nanoparticle or silver sulfide (Ag2S) nanowire networks. Top row: scanning electron microscope (SEM) images of different types of networks. (A) nanoparticle thin-film network (scale bar = 5 μm, insert = 200 nm), (B) dendritic or fractal network (scale bar = 30 μm), (C) high-density, seed-patterned nanowire network (scale bar = 50 μm). Bottom row: power-law relationships in memristive (atomic) switches and atomic switch networks. (D) power spectral density (PSD) of simulated data for a single atomic switch (red) compared to multiple atomic switches embedded in a network (blue), (E) comparison of power-law distributions between PSD plots of a purely ohmic network with no atomic switch (gray), and experimental (black) and simulated (blue) atomic switch networks, (F) probability distribution of temporally metastable conduction states over single (blue) and multiple (black) signal pulses. Partially adapted from [72, 80, 81].
2.2. Nanowire networks

Nanowire-based atomic switch networks (figure 1(B) and (C)) rely on interactions between network elements. However, nanowire networks differ from nanoparticle networks (figure 1(A)) in their morphology and connectivity. Nanowire networks can be tuned to control for nanowire thickness, extent of branching, and regional nanowire density [86]. Nanowire networks also exhibit higher levels of connectivity than nanoparticle networks. Each nanowire has the potential to engage in multiple connections with other wires elsewhere in the network, generating long-range connections between wires that would not otherwise interact and enabling recurrent connectivity loops. In contrast, nanoparticle networks rely upon nearest-neighbor interactions. Furthermore, nanowire connections are regulated by the amount of activity experienced by the nanowire-nanowire junction [70]. The high density of atomic switches, functioning as synthetic synapses, in nanowire networks (~10^8 synthetic synapses per square centimeter) further reinforces their structural similarity to synaptic networks between neurons in the brain, e.g. in the neocortex [81]. In addition to synaptic behavior similarities, nanowire networks have demonstrated fractal geometries, power-law behavior (figures 1(D)–(F)), memory, and long-range spatio-temporal correlations [87]. Importantly, the neuromorphic properties of nanowire networks are observed for different materials [71], suggesting their dynamics and information processing capacity are robust to variations in the atomic switch junctions.

2.3. Information processing

The intrinsic complexity and interconnectivity of neuromorphic networks have demonstrated a means of distributed computation in materio, which refers to a phenomenon in which the physical changes in the network are capable of performing computational tasks [88–91]. These properties can be harnessed by treating the network as a dynamic reservoir capable of mapping input signals into higher dimensions for complex computational tasks. This is achieved through a technique called reservoir computing (RC), a modification of recurrent neural network frameworks. RC enables the use of a simple readout mechanism from the network which can be employed to map the higher dimension outputs onto a desired task [91–94]. This method is advantageous in that it only requires weighting and manipulation of the output layer, greatly reducing the training cost and improving power efficiency in contrast to conventional computing architectures. Consequently, neuromorphic networks have been extensively explored as a suitable substrate for RC and have successfully realized high fidelity, low power implementation of both simple and complex tasks, including logic tasks, T-maze tests, speech recognition and associative memory among others [95–99].

Simulation-based studies also lend support to the experimental data, demonstrating several information processing and learning tasks implemented in the RC framework, including chaotic time series prediction, memory capacity, transfer learning, and multitask learning [99–104]. Indeed, one study reported that neuromorphic nanowire networks prepared in an edge-of-chaos state (i.e. a phase transition between stable and unstable dynamics) perform better in tasks of greater computational complexity [105]. A similar result was found in another study using spiking neuromorphic networks prepared in a critical state [106]. Information dynamics (e.g. transfer entropy) has also been found to be maximized when nanowire networks transition from a quiescent to an active phase [102, 107, 108]. Task performance, combined with other network properties demonstrate that nanowire networks can perform reservoir computation and other information processing paradigms. Simulations of these networks suggest their optimal performance may arise from operating at a
Figure 3. Current–voltage ($I-V$) by AC triangular input at 1 Hz and $+/-1$ V amplitude resistive switching and fluctuations, as well as chaotic attractor dynamics with increasing number of cycles: (A) cycles 1–3; (B) cycles 10–20; (C) cycles 1–100.
critical regime [74, 95, 109]. Our perspective is that this makes neuromorphic nanowire networks a unique physical system for studying critical dynamics.

3. Critical dynamics in nanowire networks

Characteristics of criticality have been observed in both Ag$_2$S and Ag-PVP nanowire networks. Experimental measurements as well as theoretical and simulation studies revealed persistent current fluctuations with a power-law PSD over several decades in frequency [73, 77, 80, 81, 110]. However, as mentioned earlier, power-law relationships, while necessary, are not sufficient to designate a system critical.

Recent studies found evidence for avalanche criticality in Ag-PVP nanowire networks [105]. It is our perspective that evidence for avalanche criticality should also exist in other types of neuromorphic nanowire networks. To test this, we considered a silver selenide (Ag$_2$Se) nanowire network. Silver selenide nanowire networks can be synthesized by drop-casting (see supporting information S1 (https://stacks.iop.org/JPCOMPLEX/2/042001/mmedia)) nanowires onto a microelectrode array (MEA). Figure 2 shows images of a MEA and the resulting drop-cast network. The highly inhomogeneous morphology of the nanowire network, as seen in figure 2 (right panel), specifically those regions of higher density and varying degrees of interconnectivity, bears some structural similarity to the neuropil of the biological neocortex [81].

Figure 3 shows current–voltage ($I$–$V$) phase diagrams acquired over many cycles of a 1 Hz triangular input wave. Several observations can be made. Firstly, each cycle forms a closed bipolar hysteresis loop pinched at the centre. This nonlinear (non-ohmic) electrical response is a key characteristic of memristive devices and reflects their memory property—i.e. the current state $I(t)$, $V(t)$ depends on the history of states prior to $t$ [111–114]. In this network, individual nanowire-nanowire intersections are memristive atomic switch junctions. Figure 3 indicates that, collectively, these junctions act like a single memristive element. A second observation from figures 3(A) and (B) is that some cycles exhibit fluctuations and hard switching (i.e. a very sharp increase or decrease in $I$). Switching events are associated with abrupt resistance changes at individual junctions, attributable to the formation/degradation of conductive filaments. A third observation is that each $I$–$V$ cycle deviates slightly from previous cycles. Indeed, no two trajectories completely coincide. Similar chaotic attractor dynamics was previously observed in memristor devices and memristive networks of Ag-PVP nanowires [105, 115]. Note, however, that the trajectories do not diverge sufficiently to qualify as chaotic. Their confinement to a localised region of phase-space instead suggests chaotic attractor dynamics. Such dynamics may be useful for computation as outputs $I(t)$ for each AC cycle represent separable features and the collective attractor dynamics suggest solutions converge to local stable states [116, 117]. Further investigation is warranted to determine (e.g. via Lyapunov exponent analysis) if these trajectories are consistent with the edge-of-chaos state, or the state where the maximal Lyapunov exponent is approximately zero. This state has been purported to be optimal for information processing [118–120]. Hochstetter et al showed that Ag-PVP
nanowire networks tuned into an edge-of-chaos state performed better on reservoir learning tasks with higher computational complexity [105].

When driven by a DC bias, fluctuations and switching events in Ag$_2$Se nanowire networks were observed to persist on timescales of many hours, as shown in figure 4. The magnified inset in figure 4(A) reveals many events where changes in $I(t)$ exceed a defined threshold (5%) over the course of a few minutes. The PSD in figure 4(B) exhibits a distinctive power-law shape, $x^{-\beta}$, with more low-frequency power potentially indicative of temporal correlations or other collective effects.

Figure 5 shows avalanche statistics determined from the $I(t)$ data in figure 4(A). The exponents of maximum likelihood (ML) power-law fits to $P(S)$ and $P(T)$ are $\tau_S = 1.89 \pm 0.02$ and $\tau_T = 2.12 \pm 0.04$, respectively. The exponent of $\langle S(T) \rangle$ is $\gamma = 1.23 \pm 0.04$, which is consistent with that predicted by the crackling noise dynamical scaling relation $(\tau_T - 1)/(\tau_S - 1) = 1.26 \pm 0.05$, within uncertainties, thus confirming avalanche criticality [121]. The critical exponent $\gamma = 1.23$ differs from the PSD exponent $\beta = 1.7$, which reflects the inhomogeneous nature of nanowire networks. In homogeneous many-body systems, the mean field approximation (e.g. random field Ising model) predicts a relation between $\gamma$ and $\beta$ [122]. The critical exponents found for avalanches in Ag$_2$Se nanowire networks differ from those in Ag-PVP nanowire networks ($\tau_S = 2.1$ and $\tau_T = 2.3$) [105] and Sn nanoparticle networks ($\tau_S = 2.0$ and $\tau_T = 2.6$) [84], which adhere to the crackling noise scaling relation with $\gamma = 1.2$ and 1.6, respectively. Conversely, it was reported that Sn nanoparticle networks demonstrate critical exponents inconsistent with the crackling noise scaling relation [123]. Different critical exponents may indicate different universality classes for these neuromorphic systems. Another possibility is that they exhibit ‘quasi-criticality’, which predicts departure from a single critical point defining a universality class along a line of ($\tau_S$, $\tau_T$) pairs that approximately obey a dynamical scaling relation [124]. Experimental measurements of Ag$_2$Se networks conducted over a much longer duration than shown in figure 4(A) (up to 72 h) exhibited avalanches with varying critical exponents during different epochs (data not shown here). This could be interpreted as quasi-criticality. Further investigation is warranted to continue exploring this idea.

4. Summary

In this perspective, we proposed that neuromorphic networks represent a unique abiotic physical system for studying criticality. We reviewed existing evidence for critical or critical-like dynamics in such systems and tested this proposition further with new experiments on silver selenide nanowire networks. This neuromorphic system was found to exhibit avalanche criticality in addition to hysteresis, persistent fluctuations with a power-law distribution, and chaotic attractor dynamics. Many studies have already demonstrated the information processing capabilities of a variety of in materio neuromorphic networks. What remains to be revealed is how the neuromorphic dynamical properties determine computational abilities. This would provide proof-of-concept credibility for neuromorphic networks as a physical abiotic model system for investigating the role of critical dynamics in information processing and computational task performance.
5. Outlook

5.1. Future work: criticality and neuromorphic networks

This perspective on neuromorphic networks and criticality provided support for the claim that such networks exhibit characteristics of critical systems. One area prime for future investigation is whether neuromorphic nanowire networks demonstrate optimal information processing capabilities at or near a critical regime.

Studies in simulation have shown that information processing systems perform reservoir computation optimally when operating at or near a critical state [107, 108]. To date, this phenomenon remains unexplored in physical neuromorphic systems such as nanowire networks despite their successful implementation into RC frameworks. Our outlook on future studies of critical systems is that new insights are to be gained by investigating how neuromorphic networks perform in a variety of computational tasks when in quasi-critical, critical and non-critical states. As neuromorphic nanowire networks are stimulus driven systems, an important goal is to demonstrate tunability between quasi-critical, critical and non-critical states. Demonstrating improved information processing performance at or near criticality, would justify using these networks as an abiotic physical model to study critical dynamics in the brain.

Neuromorphic networks could enable a new artificial intelligence (AI) ‘computer’ where the training knowledge is resident in the physical structure of the nanowire network. The information in the system can adapt based on real time interactions with the environment, exhibiting emergent human-like cognition. As machine learning and AI proliferate, computers are asked to engage in a larger array of tasks previously reserved for humans (e.g. driving, medical diagnoses, financial markets, warfare), certain distinctions between the brain and computer are expected to increasingly blur. Systems explicitly designed to mimic processes previously relegated to the human domain will need to become more brain-like (i.e. more neuromorphic) in order to achieve an ever-growing list of ambitious operations. To effectively develop such computationally intelligent matter, we need to better understand those attributes crucial to conferring the brain with its various capabilities. Criticality is one such potential attribute and its role in both the brain and abiotic physical systems must be understood in order to develop next-generation technologies for machine intelligence.

Acknowledgments

The authors wish to thank members of the California NanoSystems Institute (CNSI) Integrated Systems Nanofabrication Cleanroom (ISNC) and Nano and Pico Characterization Lab (NPC) for their support for this project. A special thanks is given to Masakazu Aono of the International Center for Materials Nanoarchitectonics (MANA), National Institute of Materials Science (NIMS), in Tsukuba, Japan. ZK acknowledges support from the Australian-American Fulbright Commission. The authors also wish to thank Hirofumi Tanaka and Takumi Kotooka at the Research Center for Neuromorphic AI Hardware, Kyushu Institute of Technology, Kitakyushu, Fukuoka, Japan, for their technical advice and inspiration for the design of silver selenide nanowire networks. JKG would like to acknowledge Dante Chialvo and the late Walter Freeman III for inspirational discussions on criticality.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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