Reservoir Computing using Percolating Networks of Nanoparticles

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Summary. Percolating networks of nanoparticles (PNNs) have been postulated as suitable systems for physical reservoir computing due to their nonlinear memristive tunnel gaps and scale-free network topology. We demonstrate the computational ability of PNNs as reservoirs, and investigate the roles of their scale-free topology and heterogeneous tunnel gap sizes.

Reservoir computing (RC) has attracted significant interest as a framework for the implementation of novel neuromorphic computing systems. Originally framed as the echo state [1] (or liquid-state [2]) approach to training recurrent neural networks, the RC scheme has traditionally been used with software-based reservoirs. Literature on echo-state networks (ESNs) has demonstrated that both the reservoir size [3] and topology [4, 5] play a role in task performance. In particular, functional advantage has been attributed to larger reservoirs with small-world and/or scale-free connectivity and edge-of-chaos and/or critical dynamics.

It appears widely expected within neuromorphic literature that hardware-based reservoirs will also benefit from these topological and dynamical properties [6]. However, in systems such as electronic memristor networks, the mechanisms which couple with reservoir topology and thereby produce the reservoir dynamics are very different from those of ESNs. Thus, the effect of reservoir size and topology on the computational performance of physical RC systems is yet to be fully elucidated [7].

Here we compare the performance of several memristive reservoir models in a range of RC tasks that are chosen to highlight different system requirements. We consider regular and scale-free topologies in networks of both uniform and heterogeneous memristive tunnel gaps (MTGs), as found experimentally in percolating networks of nanoparticles (PNNs). PNNs are novel self-assembled nanoscale systems that exhibit scale-free [8] and small-world [9] topologies and critical avalanche dynamics [10].

We find that the performance of regular arrays of uniform MTGs are limited by their symmetry and consequent low output diversity. This symmetry can be broken either by a heterogeneous distribution of memristor properties or a scale-free topology, each leading to more diverse reservoir outputs and improved computational performance. The best performance across all tasks is observed for a scale-free network of uniform MTGs. We further consider task performance as a function of reservoir size and find that performance improves with size but saturates for large systems.

These results provide insight into the roles of reservoir size, MTG heterogeneity and network topology in neuromorphic reservoirs, as well as an overview of the computational performance of PNNs in a range of benchmark tasks.

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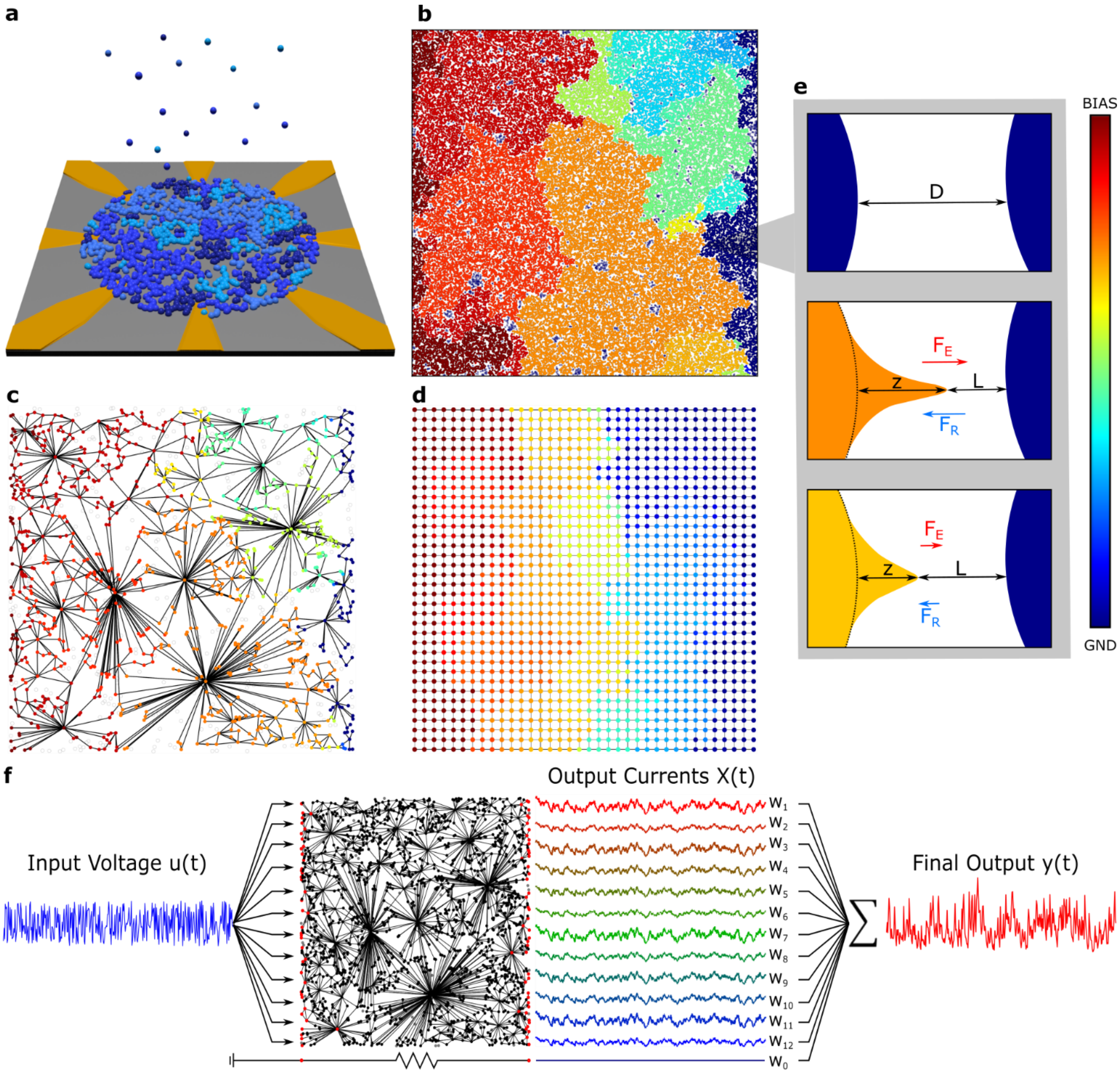

Fig. 1: (a) Schematic representation of a percolating network of nanoparticles (PNN) with multiple gold electrodes. (b) Schematic particle representation of a PNN with bias applied on the left side of the network and the right side held at ground potential. (c) Vertex graph representation of the percolating network shown in (b). Nodes represent the geometric centres of the individual groups while edges represent memristive tunnel gaps (MTGs) between group boundaries. (d) Similar graph representation of a 36x36 array network. (e) A schematic showing the growth and relaxation of a hillock in a MTG. Left: MTG with no bias applied to the network. Middle: A hillock of height z forms in response to bias applied to the left side of the network. F_E represents the electric force driving hillock growth while F_R represents the restorative force induced by surface tension. Right: Under reduced bias the hillock relaxes to a smaller height z, and both F_E and F_R decrease proportionately. (f) A schematic showing how a PNN (or array network) can be used as a physical reservoir to perform the NARMA-10 task. Input voltages are applied to all left-hand edge groups, output signals are taken from all right-hand edge groups.